

AI-Powered Nutrition: Personalized and Precise

Areeba Aslam*, Muhammad Ali Hamza, Mehmood Ahmad and Aliza Batool

Faculty of Food and Home Sciences, Muhammad Nawaz Shareef University of Agriculture, Multan.

*Corresponding author's e-mail: aslamareeba459@gmail.com

The Artificial Intelligence (AI) has transformed the world of nutrition by improving the estimation of nutrition habits, maximization of nutritional requirements, quality assessment of food, and creation of population-based health measures. AI applications such as machine learning, natural language processing and computer vision allow the analysis of complex nutritional data to be done precisely and efficiently. In personalised nutrition, AI combines personal eating habits, genome information and health data to provide personalized dietary guidelines which can be used to prevent or control chronic diseases including obesity and diabetes. Nutrient-monitoring devices and image-based dietary monitoring tools provide an even greater support to the continuous and accurate food intake tracking. In the food industry, AI-based algorithms identify quality variations, the predictive quality of the product, and supply chain safety measures. In general terms, AI is involved in terms of the contribution to the nutrition of populations, assessing nutrient shortages, and formulating policy on a large scale by analyzing high levels of dietary data. Although it offers the ability to transform a number of factors, there are still challenges that exist, especially in the areas of data privacy, bias in algorithms, and nutritional information standardization. The combination of AI and the new technologies (the Internet of Things (IoT), block chain, and precision agriculture) can also help to advance sustainable nutrition solutions. This review indicates the latest advances and areas of future advances of AI-based nutrition, with the focus on encouraging health, food security, and personalized diet control in the world.

Keywords: Artificial Intelligence (AI), machine learning, personalized nutrition, public health, food quality, precision agriculture, block-chain, sustainable nutrition, data privacy, IoT.

INTRODUCTION

AI is changing medicine and nutrition as it provides more precise, personalized, and predictive services in a clinical and community setting. AI will be used to help clinicians in diagnosing a disease, developing drugs, meal planning, and tracking the consumption of individual nutrients. Wearable technology, the use of big data analytics, and machine learning are some of the factors that have propelled the rapid growth of this interdisciplinary field (Al Kuwaiti et al., 2023). Risk assessment, diagnostics and medical decision-making are being redefined by AI. Artificial intelligence systems trained with imaging data may detect cardiovascular defects, cancer, and diabetic retinopathy, and clinical decision systems may be used to offer tailored treatment based on behavioral, environmental, and genetic factors (Sguanci et al., 2025). In nutrition, AI helps to detect nutritional deficiencies in cancer patients early enough so that timely interventions can be made. It combines the information about lifestyle, microbiota in the gut, and metabolic health in order to give personalized

dieting suggestions. On the basis of food composition data, AI-based systems can propose the best nutrient intake to stay healthy with the help of proteomic, metabolomic, and genomic data (Plotnikova & Bocharov, 2025).

Individual nutrition is central to the management of chronic diseases like diabetes, obesity, and cardiovascular disease which are directly related to dietary behaviour. AI allows identifying the trends in diets on a large scale, screening health surveys, and assessing the risk of malnutrition in the future to develop an evidence-based policy and optimize resources in developing countries (How & Chan, 2020). Also, AI improves food security by maximizing agriculture production, minimizing wastes, and predicting food supply chain disruptions. Its effects are further expanded through the integration of AI, mobile applications, and wearable devices, in real-time monitoring of diets. These devices gather and process real-time information, which enables AI to dynamically change nutrition advice to individuals, even in isolated or clinical locations (Papapani & Papapani, 2025). However, there are still privacy protection issues, algorithmic

Aslam, A., Hamza, M.A., Ahmad, M. & Batool, A. (2025). AI-Powered Nutrition: Personalized and Precise. *Journal of Food Processing and Nutrition Research*, 2(1), 55-77.

[Received 15 Feb 2025; Accepted 12 Apr 2025; Published 7 May 2025]



[Attribution 4.0 International \(CC BY 4.0\)](https://creativecommons.org/licenses/by/4.0/)

fairness, and regulatory issues. Model development should be inclusive to make AI tools just to different classes of people and dieting conditions [Sak and Suchodolska \(2021\)](#) note that using AI in nutrient science means that there is now a heavy computer and data-based component to nutritional research that shapes both scientific and business fields alike ([Sak & Suchodolska, 2021](#)). Nutritional researchers predict and this goal reflects, that AI will play a major role in addressing complex nutrition challenges by 2025.

The AI has brought a computational depth to the research of nutrition that has affected the academic study as well as business practices. The history of AI in nutrition started with the systems of planning of the diet in nutrition following rules and simple nutrient trackers. With the increased computational capacity and availability of data, AI started to incorporate multi-omics data sets, such as genomics, metabolomics, and proteomics, to increase the accuracy of nutrition ([Miyazawa et al., 2022](#)). Early AI uses were similar to advances in the healthcare industry especially in nutritional epidemiology where machine learning algorithms discovered dietary determinants that predicted improved health outcomes ([Lopes & Ferreira, 2020](#)). As a result, nutritional interventions could now be more personal and rely on data.

This changed in 2020s where AI-driven platforms started using sensor technology and electronic health records to customize nutritional interventions. Dietary assessment has also been transformed further with the use of deep learning and computer vision. Real-time food images can be analyzed by AI systems to estimate the size of dishes and nutrient content, providing a more accurate and friendly alternative to food diaries, which is conducted by hand ([Armand et al., 2024](#)). Similarly, in the field of nutrigenomics, AI uses genomic information to create personalized diets plans, overcoming generalized dietary plans ([Baldi et al., 2025](#)). These developments are also critical in clinical nutrition as well as prevention of long term metabolic illnesses. AI is also being used to address the global nutritional issues especially malnutrition and food insecurity. Predictive analytics enable vulnerable groups to be identified, food is distributed more efficiently, and supply chains are more resilient: all of these features are essential in low- and middle-income countries with scarce resources ([Joshi et al., 2024](#)).

Researchers currently use natural language processing (NLP) to analyze scientific literature and public health data to reveal gaps in research and also inform policy. By combining consumer buying information, wearable resolutions, and clinical data, the AI systems will be able to adjust the personalized diet plans ([Kassem et al., 2025](#)). Ethical, legal and social implications of AI in nutrition are also discussed in recent research, with references to the issue of data privacy, algorithmic bias, cultural variability of model performance among others ([Bailey, de Lousa and Heneghan, 2024](#)). Intelligent mHealth and wearable devices can support the dynamic aspect of health care provision, providing a user with

customized feedback and adaptive interventions to enhance adherence and long-term outcomes ([Cote & Lamarche, 2022](#)). With the current advances in AI, the interdisciplinary nature of its applications to behavioral science, microbiology, and agricultural technologies is introducing a novel phase of smart nutrition a data-driven ecosystem that maximizes health and sustainability at the same time ([Coates et al., 2024](#)). A review aims to map the breadth of AI innovations across both research and practical interventions in nutrition, offering insight into current capabilities and identifying gaps for future exploration ([Armand et al., 2024](#)).

Along with explaining AI's current role, reviews in these studies also review the methodology and quality of the studies they contain. As an example, in order to study AI's place in nutrition research, [Sosa-Holwerda et al. \(2024\)](#) structured their review with specific aims: evaluating AI use, grouping applications by field, tracking timeline changes and exploring health effects ([Sosa-Holwerda et al., 2024](#)). By using this approach, the review goes beyond mentioning studies; it also judges each study's scientific accuracy and potential use in real life. A review of this type is commonly divided into different thematic parts. According to [Cote and Lamarche \(2022\)](#), a well-structured review should explain AI concepts in nutrition, describe the search tactics and standards for selecting the literature and focus on main sections about AI use in the assessment of diets, personalized nutrition, clinical nutrition, public health and food behaviour ([Cote & Lamarche, 2022](#)). A section added at the end on ethics, boundaries and future suggestions helps explain how the findings fit into the bigger picture.

A rigorous literature review must therefore elucidate fundamental AI concepts, outline systematic search and selection strategies, and classify applications across domains such as diet assessment, clinical nutrition, and public health. Furthermore, it should address the ethical, technical, and methodological challenges that shape the evolving landscape of AI in nutrition ([Cote & Lamarche, 2022](#)). Categorizing AI technologies by their core functions including data mining, predictive analytics, image recognition, and decision support clarifies their respective contributions to both nutrition research and food technology ([Sak & Suchodolska, 2021](#)).

AI TECHNOLOGIES IN NUTRITION

Machine Learning and Deep Learning in Nutrition: Machine Learning (ML) and Deep Learning (DL) have emerged as transformative technologies in the field of nutrition, offering unprecedented opportunities to address both clinical and public health nutrition challenges. ML refers to algorithms that improve automatically through experience, while DL a subset of ML uses deep neural networks to simulate human-like decision-making. These methods are particularly suited to nutrition, where data is complex, multidimensional, and often individualized. One of the earliest and most practical applications of ML in nutrition is in dietary intake assessment. Traditional food diaries and



recall methods are subjective and error-prone. ML models now process data from wearables, smartphone images, and voice inputs to objectively estimate energy and nutrient intake. In a systematic review by [Armand et al. \(2024\)](#), DL models were highlighted for their superior performance in dietary classification tasks, often using food image databases to train convolutional neural networks (CNNs) for food recognition and portion estimation ([Armand et al., 2024](#)).

Deep Learning has also enabled real-time food recognition. For instance, computer vision-based DL frameworks can analyze images captured by mobile apps to predict nutritional content. [Kaushal et al. \(2024\)](#) demonstrated how DL architectures can detect micro- and macronutrient composition, even accounting for factors like food texture and preparation method ([Kaushal et al., 2024](#)). This approach helps users receive immediate dietary feedback and supports behavior modification strategies. Beyond individual diet tracking, ML is instrumental in personalized nutrition. [Panagoulas and Sotiropoulos \(2021\)](#) proposed models using biochemical markers (e.g., lipid panels, glucose levels) as features for neural networks that classify users' health profiles and recommend nutrient intakes accordingly. Such personalized approaches reflect a paradigm shift from population-level guidelines to individualized health optimization ([Panagoulas & Sotiropoulos, 2021](#)).

In addition to nutrition tracking, ML models support chronic disease prediction and management. For example, [Sharma et al. \(2020\)](#) showed how ML algorithms using hospital data can identify malnutrition risk and suggest early interventions in clinical settings. Their model successfully predicted malnutrition in cancer and geriatric populations, highlighting ML's clinical relevance ([Sharma et al., 2020](#)). The integration of m-Health (mobile health) platforms with ML has also improved accessibility and user engagement. [Liu et al. \(2023\)](#) developed an app-based nutrition management system that uses ML to analyze user habits and dynamically adjust dietary recommendations. Their system employs user feedback loops to refine the ML model continuously, enhancing personalization and adherence ([Liu et al., 2023](#)). Deep Learning's strength lies in processing unstructured data, such as food images, sensor data, and even text. DL models are being trained on vast food image datasets to achieve near-human accuracy in food identification. A study by [Yunus et al. \(2018\)](#) employed CNNs to analyze real-time food images and estimate nutrient values, demonstrating DL's utility in self-monitoring systems ([Yunus et al., 2018](#)).

Another innovation is the use of ML in nutritional genomics. Here, ML models correlate genetic data with dietary response patterns. These tools enable clinicians to tailor interventions for metabolic diseases, food allergies, or nutrient sensitivities. As highlighted by [Zhou et al. \(2019\)](#), DL has proven effective in modeling gene-diet interactions, thus supporting the rise of precision nutrition ([Zhou et al., 2019](#)). In public health nutrition, ML models are trained on data from national

surveys and electronic health records to identify nutrition-related disease trends, food insecurity, and population risk factors. [Tsolakidis et al. \(2024\)](#) reviewed ML applications in population-wide dietary planning and intervention mapping, emphasizing their use in identifying underserved populations and tailoring outreach efforts ([Tsolakidis et al., 2024](#)). Importantly, ML and DL also support food system innovation, from quality assurance in food production to nutrient fortification strategies. Algorithms can assess food structure, detect adulteration, or optimize nutrient content during processing. This represents a significant leap in aligning food technology with nutritional science. However, despite these advances, several challenges persist. ML models require large, well-annotated datasets, which are often lacking in nutrition research. Moreover, bias in training data can limit generalizability across diverse populations. Interpretability remains a hurdle, particularly with DL models that operate as "black boxes." These limitations underscore the importance of transparent model design and cross-disciplinary collaboration ([Cote & Lamarche, 2022](#)).

Natural Language Processing (NLP) in Nutrition: Natural Language Processing (NLP), a subfield of artificial intelligence, focuses on enabling machines to understand and generate human language. In nutrition, NLP is increasingly being used to automate the extraction, classification, and interpretation of dietary information from unstructured text sources. These include food diaries, nutrition labels, social media, clinical notes, and scientific literature. As described by [Cote and Lamarche \(2022\)](#), NLP represents a critical tool in modern nutrition science, bridging the gap between textual data and structured health applications ([Cote & Lamarche, 2022](#)). One of the key uses of NLP is in dietary pattern analysis, where it processes self-reported food intake. [Choi et al. \(2022\)](#) applied NLP to extract dietary information from health apps and online dietary logs, enabling automatic pattern recognition of food combinations and consumption frequencies ([Choi et al., 2022](#)). This method reduces reliance on manual coding and improves consistency in analyzing large-scale diet records.

NLP is also advancing the automation of food labeling and classification. [Hu et al. \(2023\)](#) developed a model using pre-trained language transformers to categorize packaged food items and predict nutritional quality by analyzing ingredient lists and marketing claims ([Hu et al., 2023](#)). This application is particularly useful for regulating food advertising and aiding consumers in healthier decision-making. In the context of food behavior analysis, NLP enables the study of public sentiment around dietary trends. [Molenaar et al. \(2024\)](#) conducted sentiment and emotion analysis on nutrition-related content shared on social media, using NLP to assess attitudes toward food, cooking, and health trends ([Molenaar et al., 2024](#)). These insights help nutrition professionals tailor messaging and interventions that align with public perceptions.



The use of NLP extends to spoken language processing for nutrition monitoring. Van Erp et al. (2021) integrated NLP with AI to analyze speech transcripts from recipe videos and food logs to assess nutritional sustainability and dietary quality (Van Erp et al., 2021). Similarly, Korpusik and Glass (2017) developed spoken language understanding models that can interpret food diaries dictated by users, improving accessibility for populations with literacy barriers or disabilities. A more novel domain of application is interactive nutrition coaching. Voice-enabled systems embedded with NLP capabilities are being deployed as conversational agents to assist users in dietary tracking and guidance. These virtual assistants can parse spoken or written queries, respond with nutritional advice, and adapt to user preferences over time, offering a dynamic and personalized experience.

NLP also plays a pivotal role in literature mining and evidence synthesis. Researchers can use NLP algorithms to scan vast repositories of scientific publications to extract nutrition-related data, detect emerging research themes, and identify gaps. This accelerates systematic review processes and enables more timely policy responses. Beyond structured applications, NLP is increasingly used in game-based interventions for nutrition education. Okpanachi and Adaji (2024) analyzed language used in serious nutrition games and found NLP capable of identifying user sentiment, engagement levels, and learning outcomes (Okpanachi & Adaji, 2024). This integration offers insights into how users emotionally connect with nutrition content. Despite its promise, NLP in nutrition faces challenges, including the complexity of food language, cultural variations, and inconsistencies in food naming. Efforts to build standardized ontologies and training datasets are ongoing to improve model accuracy and reduce bias. Cross-disciplinary collaboration between nutritionists, linguists, and computer scientists will be key to overcoming these hurdles.

Computer Vision and Image Analysis in AI-Driven Nutrition: Computer vision (CV), a subfield of artificial intelligence (AI), enables machines to interpret and process visual information. In nutrition, CV has emerged as a powerful tool for automating dietary assessment, enhancing food quality monitoring, and supporting personalized nutrition interventions. With the widespread use of smartphones and digital cameras, image-based nutritional analysis is increasingly accessible, enabling seamless integration into both clinical and consumer settings. One of the core applications of CV in nutrition is automated food recognition and classification. By analyzing images of meals, CV systems can identify food types, estimate portion sizes, and predict nutrient composition. A systematic review by Armand et al. (2024) emphasized that computer vision techniques, particularly when paired with deep learning (e.g., convolutional neural networks), can outperform traditional

methods in dietary tracking, especially in free-living environments (Armand et al., 2024).

Similarly, Kaushal et al. (2024) discussed how advanced image classification models have been trained to detect macronutrients and food groups directly from visual cues such as color, texture, and shape. These models not only enhance the granularity of nutrient estimation but also reduce user burden by eliminating manual food entry (Kaushal et al., 2024). Mobile integration of CV tools is another major breakthrough. Amugongo et al. (2022) reviewed mobile applications that use smartphone cameras and CV algorithms to estimate food volume and caloric content. These systems often employ 3D reconstruction or reference object scaling to achieve reasonable accuracy in volume estimation, which is a major determinant of caloric assessment (Amugongo et al., 2022).

A novel innovation in this space is the development of end-to-end diet management systems, such as nutritivision which use image input to guide nutrition decisions in smart healthcare ecosystems. Veeramreddy et al. (2024) proposed a system that integrates CV with nutrition databases to automatically assess food images and offer dietary recommendations in real time (Veeramreddy et al., 2024). CV also holds promise in quality control and food safety, particularly in food science. Joshi et al. (2024) highlighted the use of image analysis in identifying food adulteration, assessing product freshness, and monitoring food processing pipelines. Such applications are essential in ensuring nutritional integrity from production to consumption (Joshi et al., 2024).

In their larger analysis, Kakani et al. (2020) said that CV is now used widely in the food industry such as in equipment that recog These new solutions close the distance between what people cook and what experts suggest for a healthy diet (Kakani et al., 2020). Both technical and practical issues are holding back CV in the field of nutrition. Difficult lighting, blocked views in images, different main course dishes and a wide range of cuisines can make reading images complex. Chotwanvirat et al. (2024) tackled the issue by suggesting we build new, diverse food image datasets and use hybrid approaches that include both contextual information from the user and voice input (Chotwanvirat et al., 2024). We should also worry about how protected these images are, as often they are related to someone's health. According to Olveres et al. (2021), making sure data is anonymized and ethical in computer vision systems created for nutrition is key (Olveres et al., 2021).

AI IN NUTRITIONAL ASSESSMENT

Image Recognition for Dietary Intake Estimation in Nutritional Assessment: The integration of image recognition technologies with artificial intelligence (AI) has transformed how dietary intake is assessed. Traditional self-reporting methods, like food diaries and 24-hour recalls, are prone to recall bias and underreporting. AI-driven image-



based food logging applications now offer a promising alternative by automating food identification, portion estimation, and nutrient analysis from meal photographs. These tools enhance accuracy, reduce participant burden, and support real-time feedback, especially in mobile health settings. A major breakthrough in this area is the application of deep learning models, particularly convolutional neural networks (CNNs), for food detection and segmentation. In a systematic review, [Armand et al. \(2024\)](#) emphasized the growing role of such AI models in dietary logging, highlighting their use in tray meal detection, food classification, and caloric estimation within clinical and community settings ([Armand et al., 2024](#)).

Food logging apps powered by AI are increasingly common. [Li et al. \(2024\)](#) compared manual food logging with AI-enabled image recognition across 29 mobile apps and found that the AI-supported methods showed comparable, and often superior, performance in energy intake estimation, particularly in non-clinical, free-living conditions ([Li et al., 2024](#)). These apps often integrate with smartphone cameras to capture meals, which are then processed in real-time using pretrained food image models. The process of estimating nutrient intake from images involves several steps: food segmentation, classification, and volume estimation. [Rouhafzay et al. \(2025\)](#) reviewed tools like YOLOv2 and DeepFood, which use region-based neural networks to segment food items and estimate portion size. Such systems are especially useful for populations like individuals with diabetes, where precise carbohydrate or caloric tracking is essential for management ([Rouhafzay et al., 2025](#)).

Volume estimation remains a core challenge in image-based dietary logging. [Tahir and Loo \(2021\)](#) surveyed methods including stereo vision, depth sensors, and geometric modeling to estimate food volume from images. They noted that while accuracy has improved, mixed dishes and occluded items still pose difficulties ([Tahir & Loo, 2021](#)). Recent innovations combine voice input and wearable cameras with image analysis. [Zheng et al. \(2024\)](#) described how AI-enabled systems integrate voice queries with food image analysis to clarify ambiguous inputs, enhancing both usability and accuracy. Such multimodal systems improve the richness of data and user engagement in long-term monitoring programs ([Zheng et al., 2024](#)).

From a public health perspective, these tools offer scalable, cost-effective ways to monitor dietary intake in large populations. [Konstantakopoulos and Georga \(2023\)](#) explored how dietary apps can be deployed in community settings, enabling researchers to collect real-time dietary data and link it with health outcomes such as BMI and metabolic syndrome ([Konstantakopoulos & Georga, 2023](#)). Food logging apps also play a preventive role by providing users with instant feedback on their nutritional choices. [Chotwanvirat et al. \(2024\)](#) emphasized how interactive image-based logging tools encourage behavior change by offering visual and

nutritional feedback, which is more intuitive than text-based systems ([Chotwanvirat et al., 2024](#)). Importantly, the AI algorithms behind these systems are now being optimized using diverse, region-specific food datasets. This enhances the accuracy of dietary estimation across different cultural diets. [Allegra et al. \(2020\)](#) highlighted the need for continuous training of image recognition models using globally representative datasets to avoid bias in nutrient estimations ([Allegra et al., 2020](#)).

Nutrient Composition Analysis from Food Images or Text Using AI:

Nutritional assessments depend heavily on analyzing nutrients, but most methods require manual effort, use questionnaires or reports about foods eaten. The addition of image recognition and natural language processing (with AI), has improved both the speed and the correctness of labeling. Currently, AI may look at photos or descriptions of food to discover how healthy a meal is, so it can aid both people and clinicians instantly. Deep neural networks (DNNs) and computer vision allow for the detection of foods and a guess about their amount in pictures. [Chotwanvirat et al. \(2024\)](#) showed that technology based tools can reduce the work of calculating nutrient values, resulting in better tracking and reduced stress for users ([Chotwanvirat et al., 2024](#)). Those systems applied CNNs to recognize food from images after processing a large amount of labeled food photos.

The go FOODTM system uses both images of the food to estimate the food's nutrient content by matching them to a database of nutrients. As reported in 2020 by Lu et al., this system was much better at portion estimation and carbohydrate analysis for diabetic patients than manual methods ([Lu et al., 2020](#)). This approach combines technology that analyzes images with a table of food composition, letting us estimate nutrients in meals. AI can also look at and understand articles related to menu or the items available. The researchers mentioned a group of systems that translate unstructured meal information into nutrient data by distinguishing ingredients, cooking procedures and how much food people usually serve. In hospital and cafeteria routines, these models are best, as large sets of pre-entered menus can be reviewed all at once by the AI ([Zheng et al., 2024](#)).

Using multimodal AI which works with images and texts, is allowing AI to do more in nutritional assessments. In 2025, O'Hara et al. assessed whether ChatGPT could approximate nutrient estimates using meal photos with user questions. It was shown to be effective at using pictures to estimate calories and main nutrients, but it still needs work to improve predictions of micronutrients ([O'Hara et al., 2025](#)). These changes are being used to improve advisory systems for end customers in real time. [Cheng et al. \(2025\)](#) created a way to analyze a user's meal and deliver feedback on nutrition, showing if the user is getting too much or too little of important nutrients. They developed their system with deep



learning food classifiers and used the USDA nutrient databases to support their calculations (Cheng et al., 2025). Using AI for nutrient analysis helps manage diets in many clinics. Using their system in a hospital showed that it lowered the amount of manual work needed and improved the accuracy of nutrient tracking (Lu et al., 2020). Among others, monitoring such as this is particularly helpful for patients in ICU or having cancer.

But there are still issues to overcome. Wang et al. (2022) noted that food appearance differences, problems with combining varied dishes and a lack of varied data can lead to biased nutrient estimates in the diet (Wang et al., 2022). They encourage using federated learning to boost how well models work while still protecting user privacy. Ultimately, the use of AI in nutrient analysis is a big change for finding out what people eat. Such approaches can find objective and scalable solutions when image processing and text reading methods are more robust. These systems may play an important role in improving personalized nutrition, controlling chronic diseases and monitoring diets among large groups.

Smart Wearable Devices and Biosensors in AI-Based Nutritional Assessment: The integration of smart wearable technologies and biosensors with artificial intelligence (AI) is revolutionizing the field of nutritional assessment by enabling continuous, real-time monitoring of dietary intake and metabolic biomarkers. These tools reduce the reliance on self-reported data and bring unprecedented granularity to diet tracking, making them instrumental for personalized nutrition strategies and chronic disease management. Wearable biosensors are capable of detecting physiological signals such as glucose levels, hydration status, or metabolites in sweat which are then processed using machine learning algorithms to derive nutrient intake patterns. Sempionatto et al. (2021) discussed how biosensors integrated into flexible patches can monitor real-time biomarkers like lactate and glucose, feeding these data into AI systems for dynamic nutritional feedback (Sempionatto et al., 2021).

Zheng et al. (2024) emphasized the growing role of wearable's in AI-driven dietary monitoring, noting that devices such as smart watches and on-body cameras can detect meal times, chewing patterns, and even food types through acoustic and visual signals. This passive intake tracking, when combined with machine learning classification models, eliminates much of the cognitive and behavioral burden on the user (Zheng et al., 2024). Shi et al. (2022) described the design of intelligent nutrition tags wearable's capable of tracking dietary behavior and linking with apps for real-time analytics. These devices are supported by AI models trained on multimodal data, including motion sensors and environmental inputs, to contextualize eating events and infer caloric and nutrient consumption (Shi et al., 2022).

The deployment of these technologies in eHealth systems is gaining traction. Romero-Tapiador and Lacruz-Pleguezuelos (2023) introduced the AI4FoodDB, a platform integrating

wearable data with AI for real-time personalized health insights, including dietary monitoring, energy expenditure, and nutrient optimization (Romero-Tapiador & Lacruz-Pleguezuelos, 2023). Beyond physical activity tracking, continuous glucose monitors (CGMs) are among the most advanced wearable biosensors used in nutrition research. Limketkai et al. (2021) highlighted how CGMs, when integrated with dietary logging apps, help establish glycemic response profiles to different foods data that AI can analyze to generate tailored glycemic load recommendations (Limketkai et al., 2021).

Smart wearables are not limited to research or clinical contexts. Consumer-grade devices like smart rings, fitness bands, and sensor-equipped earbuds are increasingly used in digital wellness platforms. Prasad et al. (2025) discussed how these wearables, when integrated into AI-driven apps, allow users to receive dietary advice based on behavioral and physiological data in a non-invasive, user-friendly format (Prasad et al., 2025). The convergence of wearable sensing, AI, and the Internet of Medical Things (IoMT) enables continuous data transmission to healthcare providers. Coman et al. (2024) explored how such systems enhance diet-related disease management by delivering predictive analytics and alerts based on nutrient deficiencies, abnormal intake patterns, or biometric thresholds (Coman et al., 2024). Challenges persist, particularly around data accuracy, standardization, and privacy. As Skinner et al. (2020) noted, interpreting noisy sensor signals especially from wearable cameras or microphones requires sophisticated AI models that are still evolving (Skinner et al., 2020). Furthermore, since user data is important, requiring strict rules for ethics and regulation is key in setting up nutrition platforms for wearables.

AI FOR PERSONALIZED NUTRITION

AI-Powered Precision Nutrition: Leveraging Genomics, Microbiome, and Biomarkers: Artificial Intelligence (AI) is transforming nutrition science by enabling precision dietary recommendations tailored to an individual's genomic profile, microbiome composition, and biomarker data. Unlike conventional dietary guidelines that adopt a "one-size-fits-all" approach, precision nutrition personalizes interventions based on biological individuality. AI facilitates this by integrating large-scale, heterogeneous data and deriving actionable insights. One of the key elements in precision nutrition is genomic data, which reveals how individuals metabolize nutrients, respond to dietary patterns, and predispose to diet-related diseases. Zainab et al. (2025) demonstrated how deep learning algorithms can predict personalized dietary responses based on genetic polymorphisms, such as those related to lipid metabolism or glycemic control (Zainab et al., 2025). These AI models optimize dietary macronutrient distribution and recommend targeted nutrient supplementation.



The gut microbiome is another cornerstone in AI-driven nutrition. It acts as a metabolic and immunological interface, influencing digestion, inflammation, and even mood. [Saxena et al. \(2024\)](#) explained how AI analyzes metagenomic data to identify microbial signatures that correlate with dietary habits and chronic diseases. By understanding these relationships, AI can recommend microbiome-friendly diets that promote health and prevent dysbiosis ([Saxena et al., 2024](#)). Moreover, AI enables biomarker-guided nutrition, using clinical variables such as blood glucose, lipid profiles, or inflammatory markers to assess nutrient needs and dietary tolerability. [Pokushalov et al. \(2024\)](#) detailed how AI can integrate multi-omic biomarker data, such as metabolomics and proteomics, to generate real-time dietary advice that aligns with physiological status ([Pokushalov et al., 2024](#)). Real-world implementations of these strategies are underway. [Connell et al. \(2021\)](#) showed that AI-informed diets, generated by analyzing host and microbial gene expression, improved blood sugar levels and inflammation markers in patients over a four-week intervention. Their findings highlight how personalized diets can yield measurable improvements in clinical outcomes ([Connell et al., 2021](#)). AI is not only analyzing but also predicting diet-induced metabolic responses. [Bianchetti et al. \(2023\)](#) used AI to associate specific microbiota changes with dietary interventions, demonstrating how fiber-rich or polyphenol-rich foods alter gut ecology and affect host metabolism. Their study supports AI's capacity to model diet-microbiome-host interactions ([Bianchetti et al., 2023](#)). Integrating these multi-source data streams into nutrition platforms requires sophisticated computational infrastructure. [Yang et al. \(2024\)](#) provided a framework that fuses genomics, microbiota profiles, and dietary inputs using machine learning pipelines, enhancing prediction accuracy of nutrient requirements and health outcomes ([Yang et al., 2024](#)). Such systems are also gaining traction in managing specific conditions. [Hurtado-Lorenzo et al. \(2020\)](#) piloted AI-driven dietary recommendations for inflammatory bowel disease (IBD), identifying microbiome and inflammatory biomarkers responsive to diet. Their AI system generated personalized anti-inflammatory diets with measurable therapeutic benefits ([Hurtado-Lorenzo et al., 2020](#)). While these advances are promising, challenges remain around data privacy, algorithm transparency, and cross-population generalizability. [Baldi et al. \(2025\)](#) emphasized the importance of ethical frameworks and diverse data sources to avoid reinforcing existing health disparities in AI models ([Rouskas et al., 2025](#)).

AI-Driven Platforms for Tailored Meal Planning: Artificial Intelligence (AI) has revolutionized meal planning by transforming static dietary guidelines into dynamic, personalized nutrition systems. AI-driven platforms combine user data-such as dietary preferences, health conditions, fitness goals, and even genomic data-with machine learning algorithms to deliver meal plans that are adaptive, evidence-

based, and user-specific. These systems are redefining how individuals engage with food, shifting from manual meal preparation to automated, real-time dietary optimization. One of the most impactful applications of AI in this domain is the ability to interpret complex nutritional data and transform it into personalized meal recommendations. As outlined by [Prasad et al. \(2025\)](#), platforms now incorporate wearable data, food logs, and user feedback to develop nutrition plans tailored to individual lifestyles, improving adherence and health outcomes ([Prasad et al., 2025](#)).

[Shajith and Jaitly \(2025\)](#) introduced an AI-powered nutrition tracking system that not only identifies food types and calculates nutrient composition but also recommends daily and weekly meal plans based on caloric requirements and food availability ([Shajith & Jaitly, 2025](#)). Their system integrates real-time feedback, enabling continuous updates to meal suggestions as users log meals or physical activity. [Kahalkar and Vyas \(2024\)](#) discussed the integration of meal planning AI in digital health apps like Noom, which use AI to balance macro- and micronutrient targets while adapting to changing user behavior. These tools go beyond calorie tracking and aim to instill long-term healthy eating habits by aligning with behavioral psychology principles ([Kahalkar & Vyas, 2024](#)).

Platforms like those reviewed by [Mehrotra and Mehrotra \(2024\)](#) utilize deep learning to fine-tune meal planning based on biomarkers such as blood sugar, cholesterol, or sleep patterns. Their study showed that AI-enhanced platforms could deliver more precise nutrition advice, reducing the burden of dietary decisions for people with diabetes or cardiovascular conditions ([Mehrotra & Mehrotra, 2024](#)). [Banka et al. \(2025\)](#) proposed an AI and machine learning-based system for precision wellness. This platform synthesizes user-reported dietary preferences, allergy profiles, and even genomic information to generate meal plans optimized for health outcomes, such as reducing inflammation or improving metabolic efficiency ([Banka et al., 2025](#)).

The potential of these platforms also extends to public health and education. [Ojo et al. \(2025\)](#) highlighted an AI-based nutrition education tool aligned with WHO dietary guidelines, designed to generate meal plans for diverse populations while promoting dietary literacy. Their work underscores AI's role in scalable health promotion ([Ojo et al., 2025](#)). From a technological standpoint, these platforms often integrate natural language processing (NLP) for user interaction, computer vision for food identification, and recommender systems for adaptive learning. [Ajayi \(2025\)](#) showcased a meal planning app that leverages NLP to process user preferences and suggest personalized recipes based on health goals and seasonal food availability ([Ajayi, 2025](#)). Despite their promise, AI meal planners face challenges related to cultural dietary diversity, data privacy, and user engagement. [Gami et al. \(2024\)](#) recommended increased inclusivity in training



datasets and emphasized the need for transparent, explainable AI to build user trust, particularly in clinical nutrition contexts (Gami et al., 2024).

AI-Driven Predictive Models for Malnutrition Risk: Malnutrition remains a significant global health issue, affecting vulnerable populations such as children, the elderly, cancer patients, and those in low-income regions. Traditional screening tools like BMI and manual nutritional risk scores are often limited in scope, subjective, and poorly adapted across demographic groups. With the rise of artificial intelligence (AI), researchers are now developing predictive models that can dynamically assess malnutrition risk using a diverse range of inputs including medical records, socio demographic data, and biomarkers. In one of the earliest efforts, How and Chan (2020) introduced a human-centric AI model that utilized health and population statistics to forecast global malnutrition risk. Their model was designed to inform national and international nutrition strategies by incorporating big data from health systems and food availability metrics (How & Chan, 2020).

Machine learning has also been applied to childhood malnutrition prediction. Talukder and Ahammed (2020) developed a predictive framework using census and health data from Bangladesh to classify under-five children by malnutrition risk. Their algorithm, based on decision trees and support vector machines, outperformed traditional regression models in sensitivity and specificity (Talukder & Ahammed, 2020). For adult women, Turjo and Rahman (2024) implemented a statistical learning-AI hybrid model to predict malnutrition among Bangladeshi women. They showed that features like education, income, parity, and access to healthcare significantly influenced model accuracy. This model not only assessed current risk but also projected future trends for policy targeting (Turjo & Rahman, 2024).

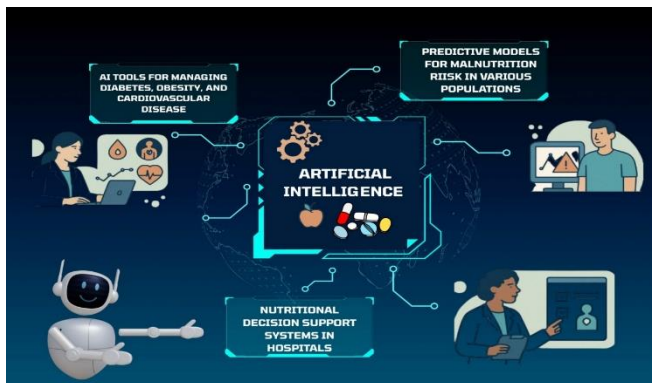


Figure 1. Artificial Intelligence in Disease management.

The elderly population presents unique challenges in malnutrition screening. Ghosh (2024) conducted a systematic review focused on AI-based malnutrition prediction in older adults, particularly within hospital settings. Models

combining clinical, biochemical, and functional data showed superior predictive value compared to standard tools like the Mini Nutritional Assessment (Ghosh, 2024). Larburu et al. (2022) built a predictive model for hospitalized older women, identifying key variables such as mobility status, cognitive impairment, and recent weight loss. Their findings highlight the importance of targeted feature selection when developing population-specific malnutrition risk tools (Larburu et al., 2022).

AI IN FOOD BEHAVIOR AND CONSUMER RESEARCH

Behavioral Pattern Recognition in Eating Habits: Artificial Intelligence (AI) is increasingly being employed to decode the complexity of human eating behaviors, enabling both researchers and health professionals to understand patterns, predict future choices, and design personalized nutrition interventions. The ability of AI to process vast and diverse datasets ranging from food images to voice inputs and diary entries makes it ideal for identifying behavioral patterns in food choices, meal frequency, emotional eating, and diet sustainability. AI-assisted platforms now allow for real-time food behavior tracking. Chew et al. (2024) evaluated an AI-assisted food app that combines image recognition with behavioral psychology metrics to monitor and improve users' eating patterns. Their mixed-methods study found improved dietary awareness and reduced emotional eating behaviors over time, supporting AI's role in behavioral transformation (Chew et al., 2024).

Image recognition technology, particularly using egocentric (first-person) camera feeds, has become central to behavior tracking. Jia et al. (2019) implemented automatic food detection using AI in egocentric images, allowing the detection of eating frequency and food types in real-world, unstructured environments. This technique is essential for capturing habitual behaviors without relying on user input, reducing recall bias (Jia et al., 2019). Citizen science platforms are also being developed to address food behavior. Casado-Mansilla (2024) introduced the SWITCH system, which integrates AI with community-led data collection to assess how social factors influence food habits. This tool provides behavior-based recommendations using machine learning insights, empowering users to change based on their unique contexts (Casado-Mansilla, 2024).

For children and adolescents, AI is being used in schools to measure food behavior. Park et al. (2022) studied the use of an AI food scanner to measure school lunch intake and correlate it with Nutrition Quotient scores. Their findings showed that early habits such as vegetable preference and food group diversity are detectable and influence long-term dietary behavior (Park et al., 2022). AI's role extends to sustainability-oriented food behavior, as shown in the work of Choi et al. (2022), who developed a deep learning model that tracks not only eating habits but also food carbon footprints. Their model promotes environmentally sustainable behaviors by linking consumption patterns to ecological outcomes,



reinforcing the interconnectedness of health and planetary wellness (Choi et al., 2022).

Understanding behavioral nuances such as emotional eating or reward-based food selection is also gaining ground. Gul et al. (2024) discussed how AI can model cognitive and emotional aspects of food behavior to design interventions targeting disordered eating and food waste reduction. These models can be incorporated into apps or therapy tools for continuous support (Gul et al., 2024). Swargiary (2025) highlighted the ethical use of interpretable AI in predicting snack choice behavior. Using machine learning, they predicted snack selection with high accuracy based on time of day, stress levels, and socioeconomic factors. This shows AI's ability not only to observe but to anticipate behavioral outcomes (Swargiary, 2025).

Joshi et al. (2024) demonstrated how AI can cluster consumers into behavioral archetypes such as health-conscious eaters or convenience-driven snackers based on consumption data and dietary pattern recognition. This segmentation aids in tailoring nutritional messaging and product development to distinct consumer personas (Joshi et al., 2024). Lastly, Samad et al. (2022) reviewed AI functionalities in food tracking apps, showing that the most effective platforms used behavioral feedback loops. These include personalized meal suggestions, reminders based on historical eating times, and nudges for healthier alternatives. The ability to learn from past data and adapt makes these tools highly effective for long-term habit formation.

Cancer patients are another high-risk group where malnutrition can significantly affect treatment outcomes. He reviewed AI-based tools for managing nutritional risk in oncology. They emphasized how deep learning models could synthesize clinical notes, lab data, and diet logs to flag early signs of cachexia or malnutrition, thereby enabling timely intervention (Sguanci et al., 2025). However, the deployment of these models in real-world health systems is not without challenges. Liou et al. (2024) investigated bias and calibration issues in a widely used malnutrition risk model, finding that predictions were less accurate for Black and Hispanic patients. Their work calls for ethical AI practices and diverse datasets to ensure equitable health outcomes (Liou et al., 2024). In a promising development, Alam et al. (2025) presented a hybrid model (SAM) that combined neural networks with ensemble methods for predicting severe acute malnutrition in under-five children. Their model demonstrated strong generalizability and was validated across multiple datasets, showcasing AI's potential for population-wide deployment (Alam et al., 2025). Lastly, Shi and Zhang (2025) developed a Random Forest-based nutrition risk model using extensive dietary, socioeconomic, and biometric datasets from over 700 individuals. Their model achieved over 90% accuracy in predicting malnutrition risk, suggesting that ensemble learning methods are well-suited for complex health classification tasks (Shi & Zhang, 2025).

AI for Tracking Emotional and Binge Eating Behaviors: Emotional eating and binge eating are complex behaviors often linked to psychological distress, mood disorders, and impulsivity. Traditional tracking methods, such as food diaries and surveys, have been limited by recall bias and underreporting. The advent of AI-powered behavioral monitoring now enables real-time, passive, and multimodal tracking of these eating patterns facilitating both self-awareness and clinical intervention. Chew et al. (2024) evaluated an AI-assisted mobile app designed to monitor emotional eating behavior through real-time tracking and feedback loops. The system used image recognition, mood logs, and push notifications to assess eating episodes and emotional triggers. Participants reported increased awareness of stress-related eating, suggesting that AI-enhanced self-monitoring promotes behavior change (Chew et al., 2024).

Digital phenotyping the use of behavioral and biometric signals collected via smartphones is being harnessed to detect binge-eating tendencies. Vega et al. (2022) conducted a study leveraging mobile interactions and wearable data to identify mental health behaviors associated with binge eating. Their AI model successfully differentiated between binge eating episodes and normal consumption patterns based on user-device interaction features (Vega et al., 2022).

AI is also being integrated into smartphone interventions for eating disorders. Linardon and Torous (2025) reviewed how machine learning algorithms, combined with ecological momentary assessment (EMA), can personalize interventions for individuals with disordered eating. Their work highlights how AI can continuously learn from user behavior, refining predictions of relapse and improving treatment responsiveness (Linardon & Torous, 2025).

Topic modeling a natural language processing technique has been used to identify online behavior patterns linked to emotional eating. Hwang et al. (2020) applied topic modeling to social media posts to uncover themes such as food cravings, mood regulation, and guilt. Their findings emphasized how language and posting behavior can serve as proxies for emotional eating patterns (Hwang et al., 2020). Behavioral prediction using AI extends to self-monitoring adherence in weight loss programs. Martinelli et al. (2020) showed that individuals with higher binge eating scores were more likely to engage with digital tracking tools. This finding challenges the assumption that binge eaters disengage from structured programs and supports the development of AI-driven tools that adapt to users' emotional states (Martinelli et al., 2020). Recent advances in real-time eating detection systems have further improved binge detection accuracy. Morshed et al. (2020) introduced a system that uses sensors to detect chewing and swallowing events, which then trigger EMA surveys to gather context on mood and food type. Such multimodal systems offer granular insights into the intersection of affect and eating behavior (Morshed et al., 2020). AI-enabled platforms are now also helping to address



maladaptive eating behaviors in mood disorders. Koning (2025) demonstrated how AI can track affective states via physiological markers and predict binge-eating episodes in individuals with mood dysregulation. These insights support more holistic, psycho behavioral models of eating behavior (Koning, 2025). Lastly, the ethical design of AI in eating disorder management is receiving attention. Ghosh et al. (2024) reviewed machine learning models used in eating disorder diagnostics and emphasized the importance of transparency, bias mitigation, and user safety. They advocate for the inclusion of explainable AI (XAI) frameworks to ensure these technologies support rather than stigmatize vulnerable users (Ghosh et al., 2024).

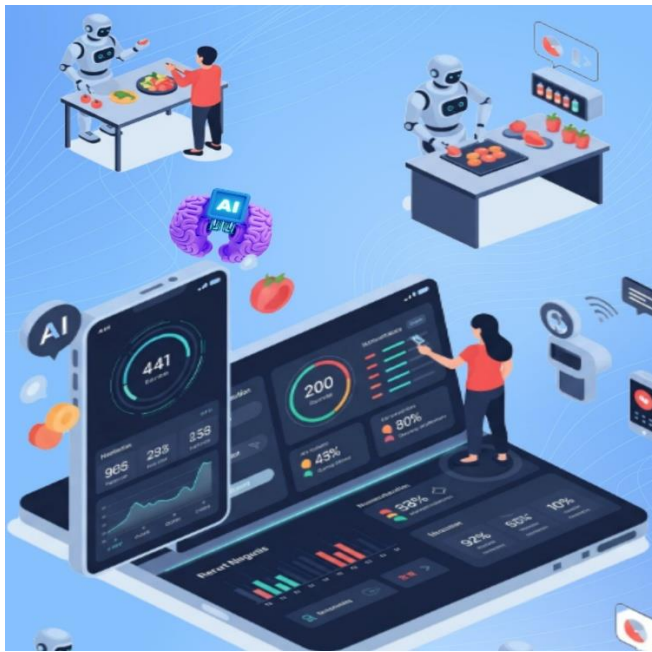


Figure 2. Artificial intelligence in nutrition assessment.

Chatbots and Virtual Nutrition Coaches: AI for Dietary Behavior Change: AI-powered chatbots and virtual coaches have gained prominence as digital tools to support healthy eating behavior, nutrition education, and weight management. By simulating human conversation and delivering context-aware guidance, these systems enable accessible, scalable, and personalized interventions. The flexibility of chatbots allows for real-time feedback, emotional support, and interactive coaching, bridging gaps in traditional health counseling. A foundational review by Chew (2022) highlights how AI chatbots support behavior change in areas such as diet and physical activity. The review revealed that these tools, designed to mimic human interaction, enhanced engagement and adherence to healthy eating plans, especially when delivering personalized messages based on user inputs (Chew, 2022).

In a proof-of-concept study, Maher et al. (2020) demonstrated the feasibility of using a virtual health coach powered by AI to promote dietary change among adults. The chatbot provided reminders, meal tips, and motivational interviewing strategies. Participants appreciated the availability and convenience, underscoring the potential for long-term adoption (Maher et al., 2020). Oh et al. (2021) conducted a systematic review of AI chatbot interventions for promoting physical activity, healthy diet, and weight loss. Their findings suggest that chatbots incorporating behavior change techniques such as goal setting, feedback, and self-monitoring were significantly more effective at improving outcomes than static apps or non-AI interventions (Oh et al., 2021).

Building on this framework, Zhang et al. (2020) introduced the AI Chatbot Behavior Change Model, which defines how chatbot interactivity, personalization, and emotional tone influence users' dietary decisions. This model serves as a design blueprint for creating more effective nutrition-focused chatbots (Zhang et al., 2020). Recent innovations focus on personalization. Calvaresi et al. (2021) developed an agent-based chatbot for nutritional coaching, which tailors meal recommendations based on dietary history, allergies, and preferences. The system uses AI to adapt to user behavior over time, offering an increasingly tailored user experience (Calvaresi et al., 2021). Tanveer et al. (2024) introduced an AI dietician chatbot that emulates dietitian-patient consultations, recommending nutrient-specific diets for conditions like hypertension and diabetes. Their system integrates macro and micronutrient databases and adapts daily based on user compliance (Tanveer et al., 2024).

In adolescent populations, Han et al. (2023) assessed the feasibility of chatbots in nutrition education and behavior coaching. Their study found that virtual coaches, when delivered via platforms like WhatsApp or Messenger, were not only feasible but highly acceptable among young users, especially when the chatbot incorporated conversational tone and gamified learning elements (Han et al., 2023). On the ethical front, Calvaresi et al. (2023) explored legal and ethical considerations for deploying virtual nutrition coaches. Key concerns include data privacy, accountability in dietary advice, and transparency of AI algorithms particularly when chatbots are used in clinical contexts (Calvaresi et al., 2023). Finally, Li (2025) presented a chatbot built with neural language models to improve dietary coaching. The chatbot used GPT-style architecture to deliver nuanced, emotionally intelligent counseling, addressing challenges like diet fatigue and motivation loss. This approach represents the future of empathetic, conversational AI in personalized nutrition (Li, 2025).

AI IN PUBLIC HEALTH NUTRITION

AI for Population-Level Dietary Surveillance in Public Health Nutrition: Artificial intelligence (AI) is rapidly transforming public health nutrition, especially in the area of population-level dietary surveillance. Traditional nutrition



surveillance systems rely on labor-intensive data collection methods, such as 24-hour recalls and food frequency questionnaires, which are time-consuming and prone to bias. AI technologies including machine learning, natural language processing, and computer vision now offer scalable, automated, and more accurate tools for monitoring food consumption and nutritional patterns across entire populations. One of the most notable applications of AI in public health nutrition is automated dietary intake monitoring. [Zheng et al. \(2024\)](#) outlined how AI-powered tools can measure food and nutrient intakes from food logs, images, or wearable devices, dramatically improving data accuracy and reducing response burden ([Zheng et al., 2024](#)). These systems are increasingly being integrated into national dietary assessments and health surveillance platforms.

In African populations, [Lo et al. \(2024\)](#) piloted an AI-enabled passive dietary monitoring system using wearable cameras. The system captured real-life dietary behaviors and processed the images with machine learning models to estimate nutrient intake. This approach brings surveillance closer to ground truth and helps address underreporting in low-resource settings ([Lo et al., 2024](#)). From a policy perspective, AI is helping bridge the gap between public health nutrition and precision nutrition. [Ordovas \(2024\)](#) emphasized the challenge of integrating individualized insights into broader dietary guidelines and proposed a balanced approach that combines large-scale AI-driven data with contextual public health goals ([Ordovas, 2024](#)).

In a broad review of AI's role in nutrition, [An and Wang \(2023\)](#) discussed how machine learning models are used to forecast nutritional deficiencies, obesity trends, and food insecurity at the population level. These insights inform real-time policy-making and resource allocation, particularly in vulnerable communities ([An & Wang, 2023](#)). Moreover, AI is central to real-time health education platforms based on WHO dietary guidelines. [Ojo et al. \(2025\)](#) introduced an AI-powered interactive platform that tailors nutrition education to specific demographic groups. The platform not only monitors dietary intake but also delivers adaptive educational content, making it a dual tool for surveillance and behavior change ([Ojo et al., 2025](#)). [Gami et al. \(2024\)](#) explored how AI supports public health interventions by identifying at-risk populations and recommending targeted nutritional strategies. Their model combines geospatial data with socioeconomic indicators to pinpoint dietary gaps and propose region-specific solutions ([Gami et al., 2024](#)).

[Naumova \(2025\)](#) proposed a taxonomy for AI and data analytics competencies in nutrition surveillance, offering guidance on how to train researchers and public health workers in the use of AI tools. This work is crucial for scaling up AI-driven dietary surveillance across health systems globally ([Naumova, 2025](#)). However, while AI offers unprecedented capabilities, challenges remain. Cultural diversity in food habits, lack of standardized datasets, and

concerns around data privacy and algorithmic bias must be addressed to ensure equitable and ethical application of AI technologies in public health nutrition.

AI models for predicting nutrition-related disease outbreaks: Artificial Intelligence (AI) has emerged as a powerful tool in the prediction and prevention of nutrition-related disease outbreaks. AI models are increasingly being deployed to analyze complex datasets encompassing dietary patterns, environmental factors, and biological markers. In a comprehensive systematic review, researchers found that AI, machine learning (ML), and deep learning (DL) are being applied across various domains in nutrition from predicting dietary inadequacies to anticipating disease trends based on nutrition-linked behaviors and biometrics ([Armand et al., 2024](#)). A critical application of AI in this space involves the early detection and surveillance of nutrition-related diseases such as obesity, diabetes, and cardiovascular disorders. According to [Roychowdhury and Chatterjee, 2024](#) AI-driven nutritional assessments are not only capable of tracking current dietary behaviors but can also predict future disease risks by integrating data from wearable technologies and real-time health monitoring systems.

The predictive modeling of foodborne illness outbreaks has also seen significant improvement due to AI. For example, algorithms can now track and anticipate contamination in supply chains, a process that dramatically reduces the risk of outbreaks. These insights are particularly crucial for vulnerable populations and can guide public health interventions ([Gami et al., 2024](#)). AI's ability to process vast and diverse datasets has made it indispensable in refining dietary assessments. AI can analyze photos of meals, track nutritional intake, and assess patterns over time to predict potential health risks such as malnutrition or diet-induced chronic diseases ([Zheng et al., 2024](#)). These assessments are significantly more accurate than traditional methods and provide individualized recommendations based on real-time feedback. Further, neural network models have been used to quantitatively assess the contribution of various risk factors to nutrition-dependent diseases.

A study by [Zaitseva et al. \(2024\)](#) demonstrated that these models could predict changes in disease probability with over 70% accuracy, emphasizing the potential of AI for disease prevention at the population level. Moreover, AI's role is expanding into population health management. AI models have been used to project hospital admissions linked to nutrition-related disorders and predict healthcare costs, enabling more strategic resource allocation ([Monlezun, 2017](#)). This macro-level application is critical in addressing public health crises and planning long-term interventions. Another emerging area is the taxonomy of AI competencies in food and nutrition security. [Naumova, \(2025\)](#) has categorized the use of AI in tracking foodborne diseases and mapping outbreak distributions, enhancing global disease surveillance systems. These models are integrated with GIS



and epidemiological data to offer a multidimensional perspective on outbreak prediction. Lastly, AI's potential is being realized through digital health platforms that combine predictive analytics with patient engagement. [Salinari et al. \(2023\)](#) emphasize that while the full integration of AI in clinical nutrition is still evolving, its potential for precise, real-time predictions in complex environments is clear. The next frontier includes AI systems capable of not only detecting and forecasting disease outbreaks but also delivering personalized dietary guidance to mitigate such risks preemptively.

Modeling food environments and access inequalities: Modeling food environments and access inequalities has become a critical focus in public health research, particularly in the context of rising chronic diseases and food insecurity. Researchers use diverse methods ranging from multilevel regression to systems science modeling to assess disparities in access to nutritious food. These models help understand how socioeconomic and spatial factors shape local food environments. For instance, [Wang et al. \(2022\)](#) employed multilevel regression models across multiple years to evaluate variations in food availability and associated social inequalities, offering insights into sustainable food environments in developing urban contexts. A central theme in modeling food environments is the concept of spatial accessibility, often captured by measures of proximity to grocery stores, fast-food outlets, or fresh produce markets. [Diehl et al. \(2020\)](#) highlighted that unequal geographic access perpetuates health disparities and emphasized the need for equity-focused modeling approaches that uncover these spatially embedded differences.

To overcome the limitations of static models, researchers are increasingly turning to systems science approaches such as

agent-based models (ABMs) and system dynamics. [Mui et al. \(2025\)](#) conducted a literature review demonstrating how simulated retail food environments (RFE) can model the dynamic, interacting components that contribute to inequitable food access such as income inequality, policy, and zoning. The home food environment also plays a role in shaping dietary habits and reinforcing inequalities. [Ranjit et al. \(2015\)](#) identified that variables such as food availability and accessibility within homes are strongly linked to socioeconomic status (SES), suggesting that food environment modeling must incorporate household-level dynamics in addition to broader community indicators. [Odoms-Young et al. \(2024\)](#) provided a critical update on the state of science linking neighborhood food environments to health disparities, highlighting racial and ethnic inequities. Their work underscores the urgent need to integrate community-based participatory methods with quantitative modeling to develop more inclusive and representative frameworks.

Spatial heterogeneity in food environments has also been observed in school neighborhoods. [Diez et al. 2019\)](#) found that children attending schools in low-SES neighborhoods were disproportionately exposed to unhealthy food environments. Their models indicated that both socioeconomic factors and built environment characteristics must be addressed to reduce exposure to fast food and ultra-processed food outlets. Beyond physical access, [Cubbin et al. \(2012\)](#) employed latent class growth modeling (LCGM) to explore the social inequalities in neighborhood food environments. They discovered that food environment quality strongly correlates with sociodemographic patterns such as income, race, and urban density.

Application Area	AI Approach	Key Features	Reference
Automated Nutrition Tracking	Multimodal sensing with machine learning (MealMeter)	Integrates wearable and mobile sensor data to estimate macronutrient intake with high accuracy.	Arefeen et al., 2025
Food Image Recognition	Deep learning with nutrition taxonomy (AI4Food-NutritionDB)	Recognizes food items using a structured nutrition taxonomy, aiding in personalized dietary assessments.	Romero-Tapiador et al., 2022
Smart Kitchen Devices	AI-powered appliances (e.g., VersaWare, Samsung AI oven)	Devices like smart cutting boards and ovens assist in nutrition tracking and cooking guidance.	Bouchard et al. 2020
Mobile Nutrition Apps	AI functionalities in apps (e.g., Foodvisor)	Evaluates AI-based features in food tracking apps, noting limited automation in most, with exceptions like Foodvisor.	Samad et al., 2022
Personalized Meal Recommendations	AI system integrating food detection and nutrition analysis (NurifyAI)	Combines computer vision and nutritional analysis to provide real-time meal recommendations.	Han et al., 2024
Precision Nutrition	AI-driven personalized nutrition plans	Utilizes AI to tailor nutrition plans based on genetics, biomarkers, and lifestyle factors.	Kassem et al., 2025
Ethical Considerations in AI Nutrition	Review of ethical issues in AI applications	Discusses concerns like data privacy, bias, and the potential dehumanization of care in AI-driven nutrition tools.	Klimova et al. 2023
AI in Malnutrition Assessment	Systematic review of AI tools in malnutrition	Highlights the limited clinical adoption of AI models in malnutrition assessment and the need for practical tools.	Janssen et al. 2024



These studies collectively reveal that a comprehensive understanding of food access inequalities requires multifaceted modeling approaches. Systems science, spatial analysis, and household-level data integration provide the best opportunity to capture the complex, often nonlinear pathways that define food environments. They also support policy simulations to evaluate potential interventions such as zoning regulations, food subsidy programs, or public-private partnerships. To build effective, equity-driven food systems, future research must further leverage interdisciplinary modeling techniques. Integrating real-time geospatial data, machine learning, and participatory mapping can amplify community voices while ensuring that interventions are context-specific and culturally relevant.

AI FOR FOOD COMPOSITION DATABASES AND LABELING

Automating data curation and standardization: Artificial Intelligence (AI) is playing an increasingly transformative role in the curation and standardization of food composition databases and labeling. With the growing complexity and volume of food data, AI is being leveraged to automate processes that were traditionally labor-intensive and error-prone. One foundational innovation in this domain is the “dataset nutrition label,” which promotes the use of standardized formats in food data collection, enabling easier integration with AI systems (Holland et al., 2020). This type of metadata ensures that models trained on such datasets are more robust and interoperable across different platforms. Automated data curation is central to improving food composition databases, where diverse data points ranging from nutrient profiles to ingredient interactions must be harmonized. AI models, particularly those using machine learning (ML), can automate the classification and quality assessment of such data, which historically required significant manual annotation (Naumova, 2025). The integration of AI into food science not only speeds up data collection but also enhances accuracy through continuous learning and validation.

Labeling is another critical area where AI is accelerating innovation. Traditional nutrition labels often contain inconsistencies due to varying regulatory requirements and human error. AI systems can standardize labeling by comparing input data against regulatory databases and identifying discrepancies. For instance, Di Bitonto et al. (2024) highlight the role of AI in matching product claims with verified nutritional data, enhancing label trustworthiness and regulatory compliance. One of the most promising applications lies in food quality control and safety assessment, where AI-powered tools automate the monitoring of food ingredient data and product labeling. These systems ensure that food labels accurately reflect compositional data, including allergen presence, nutritional claims, and origin labels (Chhetri, 2024). By automating these functions,

companies can significantly reduce mislabeling risks, which is essential for consumer safety.

Despite the advancements, data standardization remains a significant bottleneck in achieving full automation. As Sebti et al. (2025) argue, harmonized data protocols are essential to maximizing the potential of AI in food computing. In their review of IoT-integrated AI applications, they stress that data from RFID tags, QR codes, and supply chain sensors must adhere to uniform standards to be effectively processed and interpreted by AI algorithms. Deep learning and big data analytics further enhance the scope of AI in food chemistry, particularly in identifying patterns in ingredient combinations, shelf stability, and nutrient degradation. Tseng et al. (2023) describe how such technologies contribute to biodiversity tracking, supplement analysis, and automated nutrient profile generation—functions critical to maintaining comprehensive food composition databases.

From a regulatory standpoint, AI tools are becoming increasingly aligned with international labeling standards, improving transparency in both domestic and global markets. Thakkar et al. (2023) demonstrate how AI-based models enable real-time validation of labeling claims against government databases, supporting advanced food and drug safety initiatives. Yet, challenges persist. AI systems must contend with heterogeneous data inputs and insufficient training data, particularly in developing contexts. According to Magdas et al. (2025), the absence of standardized acquisition protocols can lead to discrepancies that hinder AI model performance. Addressing this requires collaborative efforts across industry, academia, and policymakers to develop and enforce global data standards.

NLP for mining scientific literature and food product information: Natural Language Processing (NLP) has rapidly emerged as a pivotal tool for mining scientific literature and food product information, particularly in the context of the exponentially growing volume of publications and unstructured data. As food science becomes increasingly data-driven, NLP techniques such as named entity recognition (NER), information extraction, and topic modeling are used to uncover relationships, trends, and hidden patterns in both scientific and commercial data repositories (Xiong et al., 2024). One of the most notable applications is the development of systems capable of parsing and classifying scientific literature to extract information on food components, nutrition claims, and health effects. Tools like Food Mine apply NLP algorithms to identify relevant content from a vast corpus of biomedical papers, extracting compositional data and health outcomes linked to food ingredients (Hooton et al., 2020). These tools fill significant gaps in traditional food composition databases, which often lag behind current research outputs.

Beyond scientific research, NLP plays a critical role in mining food product labels and regulatory documents. For instance, information extraction systems trained on FDA drug and food



labeling are used to automate the assessment of food-drug interactions and compliance issues (Shi et al., 2021). These systems improve the efficiency and accuracy of regulatory reviews by filtering large volumes of technical documentation with minimal human input. Helmick et al. (2021) illustrated the utility of NLP by applying text mining to identify literature relevant to cold denaturation—a niche yet critical phenomenon in food science. Their approach demonstrated how automated text analysis can accelerate literature reviews, highlight research gaps, and improve knowledge synthesis across disciplines.

NLP also supports consumer research by analyzing trends in food preferences, product reviews, and online discussions. Singh and Glinska-Newes (2022) utilized a Bayesian topic modeling approach to assess public attitudes towards organic foods, showing how text analytics can reveal latent sentiment drivers in large-scale datasets like social media or customer feedback. In the commercial sector, text mining has been instrumental in constructing food ontologies structured taxonomies that standardize terminology across databases. Kuzminov et al. (2018) emphasized the importance of these ontologies for linking product attributes, sensory profiles, and marketing claims, allowing for more meaningful comparisons between similar products and more intelligent food recommendation systems. Text mining also supports research in sensory science and alternative proteins. Chen et al. (2021) applied NLP to review consumer literature on plant-based proteins, revealing evolving consumer perceptions and vocabulary. These insights guide both marketing strategies and product development in emerging food categories.

Xiong et al. (2024) further argue that the scalability of NLP tools makes them uniquely suited to modern food research challenges, such as linking health claims to molecular pathways or connecting food databases with clinical trial outcomes. Their survey outlines a suite of NLP applications from document classification to knowledge graph construction. Despite its promise, NLP in food research faces several challenges, including the need for domain-specific annotated corpora and multilingual support. As Tao et al. (2020) highlight, integrating NLP systems into food research workflows requires a collaborative effort between data scientists, domain experts, and regulatory bodies to ensure accuracy, fairness, and transparency.

Enhancing food labeling accuracy and consumer transparency: Accurate food labeling and enhanced consumer transparency have become crucial concerns in the global food system, especially as consumers increasingly demand reliable information about nutritional content, sourcing, and production practices. Food labeling serves as a critical interface between consumers and producers, enabling informed decision-making and building trust. According to Gupta et al. (2025), the modern emphasis on labeling and certification stems from the need to ensure product quality while simultaneously enhancing transparency. Labeling

accuracy directly influences consumer trust and public health outcomes. As highlighted by Wu et al. (2021), food labels that include certifications and verified claims such as organic, non-GMO, or fair trade help validate consumer expectations and reduce information asymmetry. However, these claims must be rigorously verified and clearly communicated to avoid misleading interpretations.

The integration of digital tools such as Optical Character Recognition (OCR) and machine learning has introduced new capabilities for verifying nutritional claims. SP et al. (2024) demonstrate how AI technologies can cross-reference product data with regulatory guidelines to detect discrepancies and enhance transparency. Such automation reduces human error and enables large-scale monitoring of compliance. Traceability and supply chain transparency (SCT) are increasingly linked to food labeling accuracy. Nguyen & Nguyen (2025) emphasized that SCT comprising information disclosure, data accuracy, and clarity directly influences consumer purchasing behaviors. Labels reflecting the origin, processing, and sustainability of food products serve as important indicators of corporate accountability and ethical practices.

Consumer trust in labeling also depends on the readability and user-centric design of labels. Corallo et al. (2021) argue that label effectiveness is contingent not only on the accuracy of content but also on its accessibility. Labels must be intuitive, visually clear, and tailored to various levels of health literacy to effectively communicate essential product attributes. Beyond physical labels, digital and mobile-enabled labeling systems are emerging to offer layered transparency. Lam et al. (2020) suggest that transparency-enhancing technologies, such as QR codes or blockchain-based records, can complement traditional labels by linking consumers to more detailed provenance and ingredient data online. Transparency initiatives are also supported by policy frameworks and regulatory reforms aimed at safeguarding consumer interests. Gupta et al. (2025) note that modern regulations increasingly require food companies to disclose detailed nutritional, allergenic, and origin data, shifting the labeling landscape from voluntary marketing claims to mandatory declarations of public value.

However, as emphasized by Wu et al. (2021), enhancing transparency is not just about providing more information—it is about delivering the right information in a credible and understandable way. Certification schemes, third-party audits, and verified sourcing statements all contribute to a labeling ecosystem rooted in integrity and consumer empowerment. Ultimately, enhancing food labeling accuracy and transparency is a multidisciplinary endeavor, intersecting with technology, policy, behavioral science, and nutrition. As consumer demand for traceable, healthy, and ethically produced foods continues to rise, transparent labeling will remain central to fostering informed choices and building sustainable food systems.



ETHICAL, LEGAL, AND SOCIAL IMPLICATIONS (ELSI)

Data privacy and consent in dietary tracking: The Ethical, Legal, and Social Implications (ELSI) of data privacy and consent in dietary tracking applications have garnered increasing attention from 2020 to 2025, as these technologies become more integrated with health monitoring and AI systems. One of the primary concerns is user consent and the transparency of data use. Many apps fail to provide adequate information about how dietary data will be used, stored, or shared. This can result in users unwittingly consenting to practices that compromise their privacy (Ryan, 2022). The ethics of such platforms emphasize that users must have the ability to withdraw consent and that consent must be both informed and ongoing.

AI-based nutrition systems, in particular, must take extra precautions due to the sensitive nature of the data they handle. This includes not only dietary habits but also, in some cases, integration with genetic or fitness data. These expanded datasets raise the stakes for data misuse, discrimination, or biased algorithmic decisions (Naithani et al., 2025; Esmonde et al., 2023). Another ethical and legal concern involves data ownership. Most users are not aware that by using free tracking apps, they often give up ownership or control of their personal data. Recommendations have been made for app developers to adopt more robust consent protocols and privacy-by-design principles, ensuring users can access, modify, or delete their data at will (Calvaresi et al., 2023).

Moreover, wearable technologies and mobile health (mHealth) systems that support dietary tracking must ensure compliance with data protection laws such as GDPR. Studies show that many users have concerns about data sharing with third parties, yet struggle to navigate complex privacy settings (Sivakumar & Mone, 2024). To foster ethical compliance, app developers and researchers must implement frameworks for ethical data governance, ensuring transparency, consent literacy, and minimizing unintended harm through misuse of health-related data (Goodyear, 2017).

Algorithmic bias and equitable access: Algorithmic bias and equitable access are increasingly critical concerns in the deployment of health and dietary apps, particularly those driven by artificial intelligence. As these technologies become more embedded in personal health routines, ensuring fairness and avoiding discrimination becomes paramount.

Algorithmic bias refers to the systematic favoritism or exclusion of certain user groups by AI models. This bias often stems from non-representative training datasets or design assumptions. For instance, AI-driven nutrition apps frequently rely on data from predominantly Western populations, resulting in inaccuracies or irrelevant recommendations for users from underrepresented ethnic or cultural backgrounds (Prasad et al., 2025). Similarly, platforms may misinterpret diet-related behaviors when algorithms lack socio-contextual awareness (Ryan, 2022).

This bias translates into inequitable access to accurate health guidance. Marginalized populations are often at higher risk for diet-related diseases but may receive less accurate or actionable insights from apps designed without inclusivity in mind (Ojo et al., 2025). Further, these populations might lack access to premium app features or internet connectivity, exacerbating health disparities despite the growing availability of digital solutions (Henning, 2021). There is growing advocacy for ethical AI in nutrition, which entails designing systems with bias detection, demographic representativeness, and inclusive data collection. This also includes user-centered approaches that accommodate diverse socioeconomic and cultural backgrounds (Gami et al., 2024; Kassem et al., 2025).

Transparency and explain ability in AI-based nutrition tools: Transparency and explainability are foundational principles for building trust in AI-based nutrition tools, especially as these systems increasingly influence dietary choices and health behavior. From 2020 to 2025, research has highlighted the critical role of explainable AI (XAI) in improving both user trust and ethical accountability. Explainable AI is essential for helping users understand how and why a particular dietary recommendation or nutritional insight is generated. Without such transparency, users may feel disempowered or misled by opaque algorithmic decisions (Patidar et al., 2024). This is particularly crucial in healthcare contexts, where the stakes for accuracy and user trust are high. Studies argue that transparency can be achieved through model interpretability, clear documentation of data sources, and user-facing explanations of how algorithms operate. For example, tools like OBESEYE are designed with XAI methods specifically to help patients and providers interpret diet recommendations for obesity management (Roy et al., 2023). Nutrition-specific AI systems also face challenges with bias and black-box models, necessitating ethical frameworks that include transparency and explainability as core design elements. Tools that use explainability features not only perform better with user engagement but also align more closely with data governance standards (McCarthy, 2025). Furthermore, transparency is essential when integrating user data for personalized recommendations, especially when these systems collect sensitive health, diet, and biometric data. Researchers argue that XAI must also account for the social context of nutrition behaviors to be fully effective (Naithani et al., 2025).

Challenges and Future Direction: AI-based nutrition tools hold significant promise, but their progress is constrained by several critical challenges chief among them are data availability, quality, and interoperability, clinical validation, and the emerging role of generative AI. First, data challenges remain a fundamental barrier. AI tools require large, diverse, and high-quality datasets, but current nutrition datasets are often sparse, unstandardized, or lack diversity. This undermines model reliability and biases outputs, especially



for underrepresented populations (Bailey et al., 2024). Additionally, interoperability remains elusive as dietary and health records are fragmented across various platforms. The absence of shared data standards hinders seamless integration and real-time updates (Malik et al., 2025; Sharma & Kaushik, 2025).

Clinical and real-world validation of AI models is another key issue. Despite rapid development, many nutrition-related AI tools have not been rigorously tested outside controlled settings. Without validation in diverse clinical environments, their accuracy and utility remain uncertain (Goktas & Grzybowski, 2025; Shin et al., 2025). Validation also involves evaluating not just prediction accuracy but clinical impact, usability, and integration into care workflows. Looking forward, generative AI and large language models (LLMs) offer transformative potential. These systems can synthesize dietary advice, interpret food diaries, and even simulate nutritional outcomes, potentially reducing the burden on clinicians. However, risks related to misinformation, hallucinated outputs, and trust remain high without strong validation mechanisms and ethical oversight (Bennani, 2024; Vidanagamachchi & Waidyarathna, 2024).

Conclusion: The integration of artificial intelligence (AI) into nutrition science offers transformative possibilities but demands rigorous ethical, technical, and regulatory alignment. Across the landscape of dietary apps and AI-powered nutrition tools, this review has outlined key concerns and emerging directions across privacy, equity, algorithmic fairness, explainability, and clinical reliability.

Ethical, Legal, and Social Implications (ELSI): Ensuring data privacy, informed consent, and data ownership in dietary tracking systems is foundational. Ethical AI frameworks must consider sociocultural diversity and user autonomy (Ryan, 2022; Naithani et al., 2025).

Algorithmic Bias & Access: Biases in AI datasets disproportionately affect marginalized populations, creating inequities in personalized dietary guidance. Transparent, diverse, and inclusive data practices are required to ensure equitable AI interventions (Prasad et al., 2025).

Transparency & Explainability: Users and clinicians must be able to understand and trust AI outputs. Explainable AI (XAI) models not only enhance usability but are essential for accountability in health-related decision-making (McCarthy, 2025).

Technical Challenges & Future Potential: Issues around data interoperability, real-world validation, and sparse datasets hinder progress. However, generative AI and multimodal models offer new capabilities for personalized, scalable, and context-aware dietary advice (Bailey et al., 2024; Bennani, 2024). Researchers should prioritize diverse and representative datasets, develop interdisciplinary

frameworks, and embed ethics-by-design in model architecture. Clinicians must advocate for validated tools, understand XAI principles, and educate patients on interpreting AI-generated nutritional guidance responsibly. Policymakers should enforce regulations on AI transparency, data security, and equity, while fostering innovation through standardized interoperability protocols and funding for nutrition-focused AI research.

AI-driven nutrition science is poised to evolve from reactive to proactive systems-capable of tailoring interventions in real time, predicting deficiencies, and adapting to lifestyle and genetic contexts. A successful future will require human-centered, explainable, and inclusive AI that supports not replaces clinical judgment and user agency. With thoughtful governance and multidisciplinary collaboration, AI can enhance public health, reduce dietary-related diseases, and close existing nutrition inequities.

Acknowledgement: The authors would like to express their gratitude to all the researchers whose innovative research on the topic of artificial intelligence and data science and nutrition informatics has formed the basis of this review. We also wish to thank peer reviewers and editors who provided constructive criticism that helped us make the manuscript better.

Credit author statement: Conceptualization: Areeba Aslam. **Methodology:** Iza Batool, Mehmood Ahmad. **Writing - Original Draft:** Areeba Aslam, Mehmood Ahmad, Ali Hamza **Writing - Review & Editing:** Areeba Aslam, Ali Hamza, Mehmood Ahmad, Ali Hamza, Aliza Batool

Conflict of interest: The authors do not identify any conflict of interest with this work. It was a research that was carried out without the interference of commercial or institutional influence.

Ethical statement: In this article, no human or animal subject is involved since it is a review article. There was no need to have ethical approval.

Availability of data: There was no creation or analysis of any new data in this study. All data are presented in the mentioned publications and available archives which are used throughout the manuscript.

Consent to participate: Not applicable. Human respondents were not used in this study.

Informed consent: Not Applicable

Consent for publication: The final version of the manuscript has been checked and accepted by all the authors and is approved to publication.

SDGs addressed: Zero Hunger, Good Health and Well-being, Industry, Innovation, and Infrastructure.



Policy referred: The paper bases its reference on ethical AI models in accordance with the WHO Guidance on Ethics and Governance of AI to Health (2021) and FAO Digitalization to Agriculture Strategy (2023) to guarantee the responsible use of AI in customized nutrition.

Publisher's note: All claims stated in this article are exclusively those of the authors and do not necessarily represent those of their affiliated organizations or those of the publisher, the editors, and the reviewers. Any product that may be evaluated/assessed in this article or claimed by its manufacturer is not guaranteed or endorsed by the publisher/editors.

REFERENCES

- Ajayi, T. (2025). AI-powered meal planning app to support good health.
- Al Kuwaiti, A., Nazer, K., Al-Reedy, A., Al-Shehri, S., Al-Muhanna, A., Subbarayalu, A. V., & Al-Muhanna, F. A. (2023). A review of the role of artificial intelligence in healthcare. *Journal of Personalized Medicine*, 13(6), 951.
- Alam, M. M., Khan, A. I., Zafar, A., Sohail, M., Ahmad, M. T., & Azim, R. (2025). Advancing nutritional status classification with hybrid artificial intelligence: A novel methodological approach. *Brain and Behavior*, 15(5), e70548.
- Allegra, D., Battiato, S., Ortis, A., Urso, S., & Polosa, R. (2020). A review on food recognition technology for health applications. *Health Psychology Research*, 8(3), 9297.
- Amugongo, L. M., Kriebitz, A., Boch, A., & Lütge, C. (2022). Mobile computer vision-based applications for food recognition and volume and calorific estimation: A systematic review. *Healthcare*, 11(1), 59.
- An, R., & Wang, X. (2023). Artificial intelligence applications to public health nutrition. *Nutrients*, 15(19), 4285.
- Arefeen, A., Singh, S., Razavi, C., Ghasemzadeh, H., & Dev, S. (2025). Assessing the quality of reporting in artificial intelligence and machine learning research for cardiac amyloidosis. *JAMIA Open*, 8(5), ooaf104.
- Bailey, R. L., MacFarlane, A. J., Field, M. S., Tagkopoulos, I., Baranzini, S. E., Edwards, K. M., & Stover, P. J. (2024). Artificial intelligence in food and nutrition evidence: The challenges and opportunities. *PNAS Nexus*, 3(12), 461.
- Baldi, S., Sarikaya, D., Lotti, S., Cuffaro, F., Fink, D., Colombini, B., & Amedei, A. (2025). From traditional to artificial intelligence-driven approaches: Revolutionizing personalized and precision nutrition in inflammatory bowel disease. *Clinical Nutrition ESPEN*.
- Banka, R., Das, P., Das, S., & Ghosh, J. (2025). Tailored nutrition and diet plan using AI and machine learning for precision wellness. In *Harnessing AI and Machine Learning for Precision Wellness* (pp. 185-214). IGI Global Scientific Publishing.
- Bassaganya-Riera, J., Berry, E. M., Blaak, E. E., Burlingame, B., Le Coutre, J., Van Eden, W., & Serafini, M. (2021). Goals in nutrition science 2020-2025. *Frontiers in Nutrition*, 7, 606378.
- Bennani, T. (2024). *Advancing healthcare with generative AI: A multifaceted approach to reliable medical information and innovation* (Doctoral dissertation, Massachusetts Institute of Technology).
- Bianchetti, G., De Maio, F., Abeltino, A., Serantoni, C., Riente, A., Santarelli, G., & Maulucci, G. (2023). Unraveling the gut microbiome-diet connection. *Nutrients*, 15(18), 3931.
- Bouchard, B., Bouchard, K., & Bouzouane, A. (2020). A smart cooking device for assisting cognitively impaired users. *Journal of Reliable Intelligent Environments*, 6(2), 107-125.
- Calvaresi, D., Carli, R., Piguët, J. G., Contreras, V. H., Luzzani, G., Najjar, A., & Schumacher, M. (2023). Ethical and legal considerations for nutrition virtual coaches. *AI and Ethics*, 3(4), 1313-1340.
- Calvaresi, D., Eggenschwiler, S., Calbimonte, J. P., Manzo, G., & Schumacher, M. (2021). A personalized agent-based chatbot for nutritional coaching. In *Proceedings of the IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology* (pp. 682-687).
- Casado-Mansilla, D., Gomez-Carmona, O., Fernandez-de-Retana, M., Muzzioli, L., Kusar, A., Vandevijvere, S., & López-de-Ipiña, D. (2024). Food assistant for consumer behaviour change through citizen science and AI. In *Proceedings of the 9th International Conference on Smart and Sustainable Technologies (SpliTech)* (pp. 1-6). IEEE.
- Chen, Z., Gurdian, C., Sharma, C., & Prinyawiwatkul, W. (2021). Exploring text mining for recent consumer and sensory studies about alternative proteins. *Foods*, 10(11), 2537.
- Cheng, S. T., Lyu, Y. J., & Teng, C. (2025). Image-based nutritional advisory system using multimodal deep learning. *Applied Sciences*, 15(9), 4911.
- Chew, H. S. J., & Achananuparp, P. (2022). Perceptions and needs of artificial intelligence in health care: A scoping review. *Journal of Medical Internet Research*, 24(1), e32939.



- Chew, H. S. J., Chew, N. W., Loong, S. S. E., Lim, S. L., Tam, W. S. W., Chin, Y. H., & Ngiam, K. Y. (2024). Effectiveness of an artificial intelligence-assisted app for improving eating behaviors: Mixed methods evaluation. *Journal of Medical Internet Research*, 26, e46036.
- Chhetri, K. B. (2024). Applications of artificial intelligence and machine learning in food quality control and safety assessment. *Food Engineering Reviews*, 16(1), 1-21.
- Dakhia, Z., Russo, M., & Merenda, M. (2025). AI-enabled IoT for food computing: Challenges, opportunities, and future directions. *Sensors*, 25(7), 2147.
- Choi, I., Kim, J., & Kim, W. C. (2022). Dietary pattern extraction using natural language processing techniques. *Frontiers in Nutrition*, 9, 765794.
- Chotwanvirat, P., Prachansuwan, A., Sridonpai, P., & Kriengsinyos, W. (2024). Advancements in using AI for dietary assessment based on food images: A scoping review. *Journal of Medical Internet Research*, 26, e51432.
- Coates, P. M., Bailey, R. L., Blumberg, J. B., El-Sohehy, A., Floyd, E., Goldenberg, J. Z., & Weber, W. J. (2024). The evolution of science and regulation of dietary supplements: Past, present, and future. *The Journal of Nutrition*, 154(8), 2335-2345.
- Coman, L. I., Ianculescu, M., Paraschiv, E. A., Alexandru, A., & Bădăraș, I. A. (2024). Smart solutions for diet-related disease management. *Applied Sciences*, 14(6), 2351.
- Connell, J., Toma, R., Ho, C., Shen, N., Moura, P., Le, T., & Vuyisich, M. (2021). Evidence-based precision nutrition improves clinical outcomes by analyzing molecular data with artificial intelligence. [Journal details not specified].
- Corallo, A., Latino, M. E., Menegoli, M., & Pizzi, R. (2021). Assuring effectiveness in consumer-oriented traceability: Suggestions for food label design. *Agronomy*, 11(4), 613.
- Cote, M., & Lamarche, B. (2022). Artificial intelligence in nutrition research: Perspectives on current and future applications. *Applied Physiology, Nutrition, and Metabolism*, 47(1), 1-8.
- Cubbin, C., Jun, J., Margerison-Zilko, C., Welch, N., Sherman, J., McCray, T., & Parmenter, B. (2012). Social inequalities in neighborhood conditions and food environments. *Journal of Maps*, 8(4), 344-348.
- De Moraes Lopes, M. H. B., Ferreira, D. D., Ferreira, A. C. B. H., da Silva, G. R., Caetano, A. S., & Braz, V. N. (2020). Use of artificial intelligence in precision nutrition and fitness. In *Artificial Intelligence in Precision Health* (pp. 465-496). Academic Press.
- Di Bitonto, P., Magarelli, M., Novielli, P., Romano, D., Diacono, D., de Trizio, L., & Tangaro, S. (2024). From data to nutrition: The impact of computing infrastructure and artificial intelligence. *Exploration of Foods and Foodomics*, 2(6), 810-829.
- Diehl, J. A., Heard, D., Lockhart, S., & Main, D. S. (2020). Access in the food environment: A health equity approach. *Journal of Planning Education and Research*, 40(1), 69-81.
- Diez, J., Cebrecos, A., Rapela, A., Borrell, L. N., Bilal, U., & Franco, M. (2019). Socioeconomic inequalities in retail food environments around schools. *Nutrients*, 11(7), 1511.
- Esmonde, K., Roth, S., & Walker, A. (2023). Ethical framework for health information from genetics and fitness tracking data. *Technology in Society*, 74, 102297.
- Gami, S. J., Sharma, M., Bhatia, A. B., Bhatia, B., & Whig, P. (2024). Artificial intelligence for dietary management. In *Nutrition Controversies and Advances in Autoimmune Disease* (pp. 276-307). IGI Global.
- Ghosh, J. (2024). Recognizing and predicting malnutrition risk in the elderly using artificial intelligence: A systematic review. *International Journal of Advancement in Life Sciences Research*, 7(3), 1-14.
- Ghosh, S., Burger, P., Simeunovic, M., Maas, J., & Petkovic, M. (2024). Machine learning solutions for eating disorders: A review. *International Journal of Medical Informatics*, 105526.
- Goktas, P., & Grzybowski, A. (2025). Ethical clinical challenges and pathways to trustworthy AI. *Journal of Clinical Medicine*, 14(5), 1605.
- Goodyear, V. A. (2017). Social media, apps and wearable technologies: Navigating ethical dilemmas and procedures. *Qualitative Research in Sport, Exercise and Health*, 9(3), 280-294.
- Gul, K., Panicker, S., Morande, S., & Tewari, V. (2024). Tiny tech, big impact: How AI-enhanced approaches can reshape food habits and support waste reduction. In *Neuroscientific Insights and Therapeutic Approaches to Eating Disorders* (pp. 318-327). IGI Global.
- Gupta, M. K., Balodi, V., Tripathi, A. D., Agarwal, A., & Nirmal, N. P. (2025). The importance of labeling and certification: Ensuring quality and transparency. In *Unleashing the Power of Functional Foods and Novel Bioactives* (pp. 449-465). Academic Press.
- Han, R., Todd, A., Wardak, S., Partridge, S. R., & Raeside, R. (2023). Feasibility and acceptability of chatbots for nutrition and physical activity promotion among adolescents. *JMIR Human Factors*, 10(1), e43227.



- Helmick, H., Nanda, G., & Ettestad, S. (2021). Applying text mining to identify relevant literature in food science. *Journal of Food Science*, 86(4), 1082-1091.
- Henning, J. M. (2021). *User-centered design of Nutri: A clinical decision support technology to improve equity in dietary behavior change* (Doctoral dissertation).
- Holland, S., Hosny, A., Newman, S., Joseph, J., & Chmielinski, K. (2020). The dataset nutrition label. *Data Protection and Privacy*, 12(12), 1.
- Magdas, D. A., Hategan, A. R., David, M., & Berghian-Grosan, C. (2025). The journey of artificial intelligence in food authentication. *Foods*, 14(10), 1808.
- Hooton, F., Menichetti, G., & Barabási, A.-L. (2020). Exploring food contents in scientific literature with FoodMine. *Scientific Reports*, 10, 15952.
- How, M. L., & Chan, Y. J. (2020). Artificial intelligence-enabled predictive insights for ameliorating global malnutrition. *AI*, 1(1), 4.
- Hu, G., Ahmed, M., & L'Abbé, M. R. (2023). NLP and machine learning approaches for food categorization and nutrition quality prediction. *The American Journal of Clinical Nutrition*, 117(3), 553-563.
- Hurtado-Lorenzo, A., Honig, G., & Heller, C. (2020). Precision nutrition initiative for inflammatory bowel disease. *Crohn's & Colitis* 360, 2(4), otaa087.
- Hwang, Y., Kim, H. J., Choi, H. J., & Lee, J. (2020). Abnormal eating behavior patterns in online users. *Journal of Medical Internet Research*, 22(3), e15700.
- Janssen, S. M., Bouzembrak, Y., & Tekinerdogan, B. (2024). Artificial intelligence in malnutrition: A systematic review. *Advances in Nutrition*, 15(9), 100264.
- Jia, W., Li, Y., Qu, R., Baranowski, T., Burke, L. E., Zhang, H., & Sun, M. (2019). Automatic food detection in egocentric images using AI. *Public Health Nutrition*, 22(7), 1168-1179.
- Joshi, S., Bisht, B., Kumar, V., Singh, N., Pasha, S. B. J., & Kumar, S. (2024). Artificial intelligence-assisted food science and nutrition. *Systems Microbiology and Biomanufacturing*, 4(1), 86-101.
- Kahalkar, K., & Vyas, U. (2024). AI for personalized nutrition and healthcare management. In *Proceedings of the 2nd DMIHER International Conference on AI in Healthcare, Education and Industry* (pp. 1-6). IEEE.
- Kakani, V., Nguyen, V. H., Kumar, B. P., Kim, H., & Pasupuleti, V. R. (2020). Computer vision and AI in the food industry. *Journal of Agriculture and Food Research*, 2, 100033.
- Kassem, H., Beevi, A. A., Basheer, S., Lutfi, G., Cheikh Ismail, L., & Papandreou, D. (2025). AI's role in nutrition: An updated narrative review. *Nutrients*, 17(1), 190.
- Kaushal, S., Tammineni, D. K., Rana, P., Sharma, M., Sridhar, K., & Chen, H.-H. (2024). Computer vision and deep learning for food nutrient detection. *Trends in Food Science & Technology*, 104408.
- Klimova, B., Pikhart, M., & Kacatl, J. (2023). Ethical issues of the use of AI-driven mobile apps for education. *Frontiers in Public Health*, 10, 1118116.
- Koning, E. (2025). *Exploring maladaptive eating behaviors in mood disorders: From digital monitoring to psychedelic-assisted psychotherapy* (Doctoral dissertation).
- Konstantakopoulos, F. S., Georga, E. I., & Fotiadis, D. I. (2023). Image-based food recognition and volume estimation using artificial intelligence: A review. *IEEE Reviews in Biomedical Engineering*, 17, 136-152.
- Korpusik, M., & Glass, J. (2017). Spoken language understanding for a nutrition dialogue system. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 25(7), 1450-1461.
- Korpusik, M., & Glass, J. (2017). Spoken language understanding for a nutrition dialogue system. In *Proceedings of Interspeech 2017*. IEEE.
- Kumar Papasani, P., & Papasani, R. T. (2025). The use of artificial intelligence and data analytics in nutrition. [Source details not specified].
- Kuzminov, I., Bakhtin, P., Khabirova, E., Kotsemir, M., & Lavrynenko, A. (2018). Mapping radical innovations in the food industry: A text mining study. *Higher School of Economics Research Papers*, 80.
- Lam, T. K., Heales, J., Hartley, N., & Hodgkinson, C. (2020). Consumer trust in food safety requires information transparency. *Australasian Journal of Information Systems*, 24.
- Larburu, N., Artola, G., Kerexeta, J., Caballero, M., Ollo, B., & Lando, C. M. (2022). AI-based risk prediction of malnutrition in hospitalized older women. *Geriatrics*, 7(5), 105.
- Li, K. J. H. (2025). *A diet coaching chatbot using neural language models*.
- Li, X., Yin, A., Choi, H. Y., Chan, V., Allman-Farinelli, M., & Chen, J. (2024). Evaluating AI-enabled food image recognition apps for nutrition care. *Nutrients*, 16(15), 2573.



- Limketkai, B. N., Mauldin, K., Manitiuis, N., Jalilian, L., & Salonen, B. R. (2021). The age of artificial intelligence in clinical nutrition. *Current Surgery Reports*, 9(7), 20.
- Linardon, J., & Torous, J. (2025). Integrating AI and smartphone technology for eating disorder treatment. *International Journal of Eating Disorders*.
- Liou, L., Scott, E., Parchure, P., Ouyang, Y., Egorova, N., Freeman, R., & Levin, M. A. (2024). Calibration and bias of machine learning malnutrition prediction models. *NPJ Digital Medicine*, 7(1), 149.
- Liu, Y., Jiang, H., Qi, Y., & Yang, J. (2023). m-Health of nutrition using smartphone and machine learning. *Mobile Information Systems*, 2023, 3979020.
- Lo, F. P. W., Qiu, J., Jobarteh, M. L., Sun, Y., Wang, Z., Jiang, S., & Lo, B. (2024). AI-enabled wearable cameras for dietary assessment. *NPJ Digital Medicine*, 7(1), 1-16.
- Lu, Y., Stathopoulou, T., Vasiloglou, M. F., Pinault, L. F., Kiley, C., Spanakis, E. K., & Mougiakakou, S. (2020). goFOOD™: An artificial intelligence system for dietary assessment. *Sensors*, 20(15), 4283.
- Magdas, A. R., David, M., Berghian-Grosan, C., Baia, M., Vedeau, N., & Magdas, D. A. (2025). Data fusion for food authentication models. *Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy*, 127246.
- Maher, C. A., Davis, C. R., Curtis, R. G., Short, C. E., & Murphy, K. J. (2020). Virtual health coach for diet and physical activity. *JMIR mHealth and uHealth*, 8(7), e17558.
- Malik, P. K., Bhatt, H., & Sharma, M. (2025). AI integration in healthcare systems for disease detection. In *AI in Disease Detection: Advancements and Applications* (pp. 191-213).
- Martinelli, M. K., D'Adamo, L., & Butryn, M. L. (2020). Binge eating predicts adherence to digital self-monitoring during behavioral weight loss. *Eating Behaviors*, 39, 101448.
- McCarthy, D. I. (2025). Nutritional intelligence in the food system: Combining food, health, data, and AI expertise. *Nutrition Bulletin*.
- Mehrotra, A., & Mehrotra, A. (2024). Artificial intelligence in nutritional planning and diet management. *International Journal of Innovations in Science, Engineering and Management*, 259-262.
- Miyazawa, T., Hiratsuka, Y., Toda, M., Hatakeyama, N., Ozawa, H., Abe, C., & Miyazawa, T. (2022). Artificial intelligence in food science and nutrition: A narrative review. *Nutrition Reviews*, 80(12), 2288-2300.
- Molenaar, A., Jenkins, E. L., Brennan, L., Lukose, D., & McCaffrey, T. A. (2024). Sentiment and emotion analysis of nutrition-related social media content. *Nutrition Research Reviews*, 37(1), 43-78.
- Monlezun, D. J., Jr. (2017). *Artificial intelligence-driven population health management* (Doctoral dissertation, Tulane University).
- Morshed, M. B., Kulkarni, S. S., Li, R., Saha, K., Roper, L. G., Nachman, L., & Abowd, G. D. (2020). Real-time eating detection system using AI. *JMIR mHealth and uHealth*, 8(12), e20625.
- Mui, Y., Winkler, M. R., Hunt, S. L., Gittelsohn, J., & Tracy, M. (2025). Simulated retail food environments: Systems science approaches. *Obesity Reviews*, e13887.
- Naithani, K., Raiwani, Y. P., Tiwari, S., & Chauhan, A. S. (2025). Ethical aspects of AI nutrition. In *AI-Based Nutritional Intervention in Polycystic Ovary Syndrome (PCOS)* (pp. 271-290). Springer Nature Singapore.
- Naumova, E. N. (2025). AI applications for nutrition and food security research. *Nutrition Today*, 60(1), 20-29.
- Nguyen, M. H., & Nguyen, D. H. (2025). Transparency, traceability, and consumer trust in food supply chains. *Journal of Consumer Marketing*.
- O'Hara, C., Kent, G., Flynn, A. C., Gibney, E. R., & Timon, C. M. (2025). Evaluation of ChatGPT for nutrient estimation from meal photographs. *Nutrients*, 17(4), 607.
- Odoms-Young, A., Brown, A. G., Agurs-Collins, T., & Glanz, K. (2024). Food insecurity and neighborhood food environments. *The American Journal of Clinical Nutrition*, 119(3), 850-861.
- Oh, Y. J., Zhang, J., Fang, M. L., & Fukuoka, Y. (2021). AI chatbots for promoting physical activity and healthy diet. *International Journal of Behavioral Nutrition and Physical Activity*, 18, 1-25.
- Ojo, T. F., Akpor, O. A., & Talabi, Y. J. (2025). AI-powered platforms for interactive nutrition education based on WHO guidelines. *Afe Babalola University Journal of Engineering Research and Development*, 8(1).
- Ojo, T. F., Akpor, O. A., Talabi, Y. J., & Afolalu, A. S. (2025). AI-powered platforms for nutrition education: An overview. *ABUAD Journal of Engineering Research and Development*, 8(1), 161-168.
- Okpanachi, V. A., & Adaji, I. (2024). Serious games for nutrition using NLP techniques. In *Proceedings of the IEEE Computing and Communication Workshop and Conference (CCWC)* (pp. 734-743).
- Olveres, J., González, G., Torres, F., Moreno-Tagle, J. C., Carbajal-Degante, E., Valencia-Rodríguez, A., & Escalante-Ramírez, B. (2021). AI and computer vision in medical image analysis. *Quantitative Imaging in Medicine and Surgery*, 11(8), 3830-3845.



- Ordovás, J. (2024). Balancing population nutrition and precision nutrition. In *Precision Nutrition* (pp. 425-438). Academic Press.
- Panagoulas, D. P., Sotiropoulos, D. N., & Tsihrintzis, G. A. (2021). Nutritional biomarkers and machine learning for personalized nutrition. *Intelligent Decision Technologies*, 15(4), 645-653.
- Park, J., Son, K., Woo, S., Park, K. H., & Lim, H. (2022). Relationship between eating habits of elementary school students and school meal intake measured by an AI food scanner. *Journal of the Korean Dietetic Association*, 28(4), 281-292.
- Patidar, N., Mishra, S., Jain, R., Prajapati, D., Solanki, A., Suthar, R., & Patel, H. (2024). Transparency in AI decision making: A survey of explainable AI methods and applications. *Advances of Robotic Technology*, 2(1).
- Plotnikova, N., & Bocharov, A. (2025). Artificial intelligence and personalized nutrition: How algorithms facilitate balanced macro- and micronutrient intake. *Endocrinologie-Nutrition ClinicalKey Now-EMC & Outils Cliniques*.
- Pokushalov, E., Ponomarenko, A., Shraimer, E., Kudlay, D., & Miller, R. (2024). Biomarker-guided dietary supplementation: A narrative review of precision nutrition. *Nutrients*, 16(23), 4033.
- Prasad, G., Padhiary, M., & Hoque, A. (2025). AI-driven personalized nutrition apps and platforms for enhanced diet and wellness. In *Emerging Technologies in Health and Medicine* (pp. 87-110). IGI Global.
- Prasad, G., Padhiary, M., Hoque, A., & Kumar, K. (2025). AI-driven personalized nutrition apps and platforms for enhanced diet and wellness. In *Food in the Metaverse and Web 3.0 Era* (pp. 125-158). IGI Global Scientific Publishing.
- Ranjit, N., Wilkinson, A. V., Lytle, L. M., Evans, A. E., Saxton, D., & Hoelscher, D. M. (2015). Socioeconomic inequalities in children's diet: The role of the home food environment. *International Journal of Behavioral Nutrition and Physical Activity*, 12, 1-9.
- Romero-Tapiador, S., Lacruz-Pleguezuelos, B., Tolosana, R., Freixer, G., Daza, R., Fernández-Díaz, C. M., & Carrillo de Santa Pau, E. (2023). AI4FoodDB: A database for personalized e-health nutrition through AI and wearables. *Database*, 2023, baad049.
- Rouhafzay, A., Rouhafzay, G., & Jbilou, J. (2025). Image-based food monitoring for dietary management in diabetes: A scoping review. *Frontiers in Nutrition*, 12, 1501946.
- Rouskas, K., Guela, M., Pantoura, M., Pagkalos, I., Hassapidou, M., Lalama, E., & Argiriou, A. (2025). Influence of AI-driven personalized nutrition on the human gut microbiome. *Nutrients*, 17(7), 1260.
- Roy, M., Das, S., & Protity, A. T. (2023). OBESEYE: Interpretable diet recommender for obesity management using machine learning. *arXiv preprint arXiv:2308.02796*.
- Roychowdhury, P., Chatterjee, M., Bhattacharjya, A., & Lahiri, S. (2024). Potencies of AI-driven nutritional assessment in public health. *The Indian Journal of Nutrition and Dietetics*, 100-108.
- Ryan, M. (2022). The ethics of dietary apps: Technology, health, and the capability approach. *Technology in Society*, 68, 101873.
- Sak, J., & Suchodolska, M. (2021). Artificial intelligence in nutrition science research: A review. *Nutrients*, 13(2), 322.
- Salinari, A., Machì, M., Armas Diaz, Y., Cianciosi, D., Qi, Z., Yang, B., & Giampieri, F. (2023). Digital technologies and AI in nutrition assessment. *Diseases*, 11(3), 97.
- Samad, S., Ahmed, F., Naher, S., Kabir, M. A., Das, A., Amin, S., & Islam, S. M. S. (2022). Smartphone apps for tracking food consumption using AI. *Intelligent Systems with Applications*, 15, 200103.
- Saxena, R., Sharma, V., Saxena, A. R., & Patel, A. (2024). Harnessing AI and gut microbiome research for precision health. *Journal of Artificial Intelligence General Science*, 3(1), 74-88.
- Sebti, M. R., Dakhia, Z., Carabetta, S., Di Sanzo, R., Russo, M., & Merenda, M. (2025). Real-time AI-enabled IoT classification of ochratoxin A contamination. *Sensors*, 25(3), 784.
- Sempionatto, J. R., Montiel, V. R. V., Vargas, E., Teymourian, H., & Wang, J. (2021). Wearable and mobile sensors for personalized nutrition. *ACS Sensors*, 6(5), 1745-1760.
- Sguanci, M., Palomares, S. M., Cangelosi, G., Petrelli, F., Ferrara, G., & Mancin, S. (2025). Artificial intelligence in management of malnutrition in cancer patients. *Advances in Nutrition*, 100438.
- Shajith, S., & Jaitly, V. (2025). Building an AI-powered nutrition tracking system. In *Proceedings of the 2025 International Conference on Inventive Systems and Control (ICISC)*. IEEE.
- Sharma, N., & Kaushik, P. (2025). Integration of AI in healthcare systems: Challenges and opportunities for disease detection and diagnosis. In *AI in Disease Detection: Advancements and Applications* (pp. 239-263).
- Shi, S., & Zhang, H. (2025). Nutritional risk prediction based on random forest classifier. In *Proceedings of the 2025 International Conference on Intelligent Systems and Computational Networks (ICISCN)* (pp. 1-7). IEEE.
- Shi, Y., Ren, P., Zhang, Y. I., Gong, X., Hu, M., & Liang, H. (2021). Information extraction from FDA drug labeling using natural language processing. *Frontiers in Research Metrics and Analytics*, 6, 670006.



- Shi, Z., Li, X., Shuai, Y., Lu, Y., & Liu, Q. (2022). Development of wearable technologies for measuring nutrient intake toward precision nutrition. *Nutrition Bulletin*, 47(4), 388-406.
- Shin, Y., Lee, M., Lee, Y., Kim, K., & Kim, T. (2025). Artificial intelligence-powered quality assurance. *Life*, 15(4), 654.
- Singh, A., & Glińska-Neweś, A. (2022). Modeling public attitude toward organic foods using big data and text mining. *Journal of Big Data*, 9, 12.
- Sivakumar, C. L. V., Mone, V., & Abdumukhtor, R. (2024). Addressing privacy concerns with wearable health monitoring technology. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 14(3), e1535.
- Skinner, A., Toumpakari, Z., Stone, C., & Johnson, L. (2020). Future directions for objective assessment of eating using wearable sensing technology. *Frontiers in Nutrition*, 7, 80.
- Sosa-Holwerda, A., Park, O. H., Albracht-Schulte, K., Niraula, S., Thompson, L., & Oldewage-Theron, W. (2024). Role of artificial intelligence in nutrition research: A scoping review. *Nutrients*, 16(13), 2066.
- SP, S. I., Karthikeyan, L., Bhoomika, P., Tejaswi, K., Khande, L. S., & Vemishetti, N. S. (2024). Automating nutritional claim verification using OCR and machine learning. In *Proceedings of the 2024 International Conference on IoT Based Control Networks and Intelligent Systems (ICICNIS)* (pp. 1164-1171). IEEE.
- Swargiary, K. (2025). Interpretable AI for behavioral prediction: An ethical laboratory experiment on snack choice prediction. *LatIA*, (3), 324.
- Tahir, G. A., & Loo, C. K. (2021). Survey of image-based food recognition and volume estimation methods for dietary assessment. In *Healthcare* (Vol. 9, No. 12, p. 1676). MDPI.
- Talukder, A., & Ahammed, B. (2020). Machine learning algorithms for predicting malnutrition among under-five children. *Nutrition*, 78, 110861.
- Tanveer, S., Abdullah, M., Mohiuddin, S. Q., & Shareef, H. (2024). Artificial intelligence dietician chatbot. *International Journal of Information Technology and Computer Engineering*, 12(2), 759-768.
- Tao, D., Yang, P., & Feng, H. (2020). Text mining as a big data tool for food science and nutrition. *Comprehensive Reviews in Food Science and Food Safety*, 19(5), 2176-2200.
- Thakkar, S., Slikker, W., Yiannas, F., Silva, P., Blais, B., Chng, K. R., & Tong, W. (2023). Artificial intelligence and real-world data for drug and food safety. *Regulatory Toxicology and Pharmacology*, 140, 105388.
- Theodore Armand, T. P., Nfor, K. A., Kim, J. I., & Kim, H. C. (2024). Applications of AI, machine learning, and deep learning in nutrition: A systematic review. *Nutrients*, 16(7), 1073.
- Tseng, Y. J., Chuang, P. J., & Appell, M. (2023). Machine learning and deep learning in food chemistry big data. *ACS Omega*, 8(18), 15854-15864.
- Tsolakidis, D., Gymnopoulos, L. P., & Dimitropoulos, K. (2024). AI and machine learning technologies for personalized nutrition. In *Informatics* (Vol. 11, No. 3, p. 62). MDPI.
- Turjo, E. A., & Rahman, M. H. (2024). Assessing risk factors for malnutrition among women in Bangladesh and forecasting malnutrition using machine learning approaches. *BMC Nutrition*, 10(1), 22.
- Van Erp, M., Reynolds, C., Maynard, D., Starke, A., Ibáñez Martín, R., Andres, F., ... Bosma, U. (2021). Using natural language processing and artificial intelligence to explore the nutrition and sustainability of recipes and food. *Frontiers in Artificial Intelligence*, 3, 621577.
- Veeramreddy, M., Pradhan, A. K., Ghanta, S., Rachakonda, L., & Mohanty, S. P. (2024). NUTRIVISION: A system for automatic diet management in smart healthcare. *arXiv preprint arXiv:2409.20508*.
- Vega, J., Bell, B. T., Taylor, C., Xie, J., Ng, H., Honary, M., & McNaney, R. (2022). Detecting mental health behaviors using mobile interactions: Exploratory study focusing on binge eating. *JMIR Mental Health*, 9(4), e32146.
- Vidanagamachchi, S. M., & Waidyarathna, K. M. G. T. R. (2024). Opportunities, challenges and future perspectives of using bioinformatics and artificial intelligence techniques on tropical disease identification using omics data. *Frontiers in Digital Health*, 6, 1471200.
- Wang, L., He, S., Zhao, C., Su, S., Weng, M., & Li, G. (2022). Unraveling urban food availability dynamics and social inequalities in developing contexts. *Sustainable Cities and Society*, 77, 103591.
- Wang, W., Min, W., Li, T., Dong, X., Li, H., & Jiang, S. (2022). Vision-based analysis for automatic dietary assessment: A review. *Trends in Food Science & Technology*, 122, 223-237.
- Wu, W., Zhang, A., van Klinken, R. D., & Schrobback, P. (2021). Consumer trust in food and the food system: A critical review. *Foods*, 10(10), 2490.
- Xiong, S., Tian, W., Si, H., Zhang, G., & Shi, L. (2024). Applications of text mining in the food domain: A survey. *Algorithms*, 17(5), 176.
- Yang, Z., Zhu, J., Lu, W., Tian, F., Zhang, H., & Chen, W. (2024). Integrating artificial intelligence in multiscale gut microbiota-diet relations for health promotion. *Food Bioscience*, 61, 104541.



- Yunus, R., Arif, O., Afzal, H., Amjad, M. F., Abbas, H., Bokhari, H. N., ... Nawaz, R. (2018). Estimating nutritional value of food in real time using deep learning techniques. *IEEE Access*, 7, 2643-2652.
- Zainab, H., Khan, M. I., Arif, A., & Khan, A. R. A. (2025). Deep learning in precision nutrition: Tailoring diet plans based on genetic and microbiome data. *Global Journal of Computer Sciences and Artificial Intelligence*, 1(1), 31-42.
- Zaitseva, N. V., Kiryanov, D. A., Khismatullin, D. R., Chigvintsev, V. M., & Mustafina, I. Z. (2024). Quantitative assessment of nutrition-dependent disease risk factors using neural network modelling in schoolchildren. *Hygiene and Sanitation*, 103(6), 577-583.
- Zhang, J., Oh, Y. J., Lange, P., Yu, Z., & Fukuoka, Y. (2020). AI chatbot behavior change model for promoting physical activity and healthy diet. *Journal of Medical Internet Research*, 22(9), e22845.
- Zheng, J., Wang, J., Shen, J., & An, R. (2024). Artificial intelligence applications to measure food and nutrient intakes: A scoping review. *Journal of Medical Internet Research*, 26, e54557.
- Zhou, L., Zhang, C., Liu, F., Qiu, Z., & He, Y. (2019). Application of deep learning in food: A review. *Comprehensive Reviews in Food Science and Food Safety*, 18(6), 1793-1811.

